Night in the Informal City: How Limited Public Infrastructure Shapes Life After Dark in Informal Settlements

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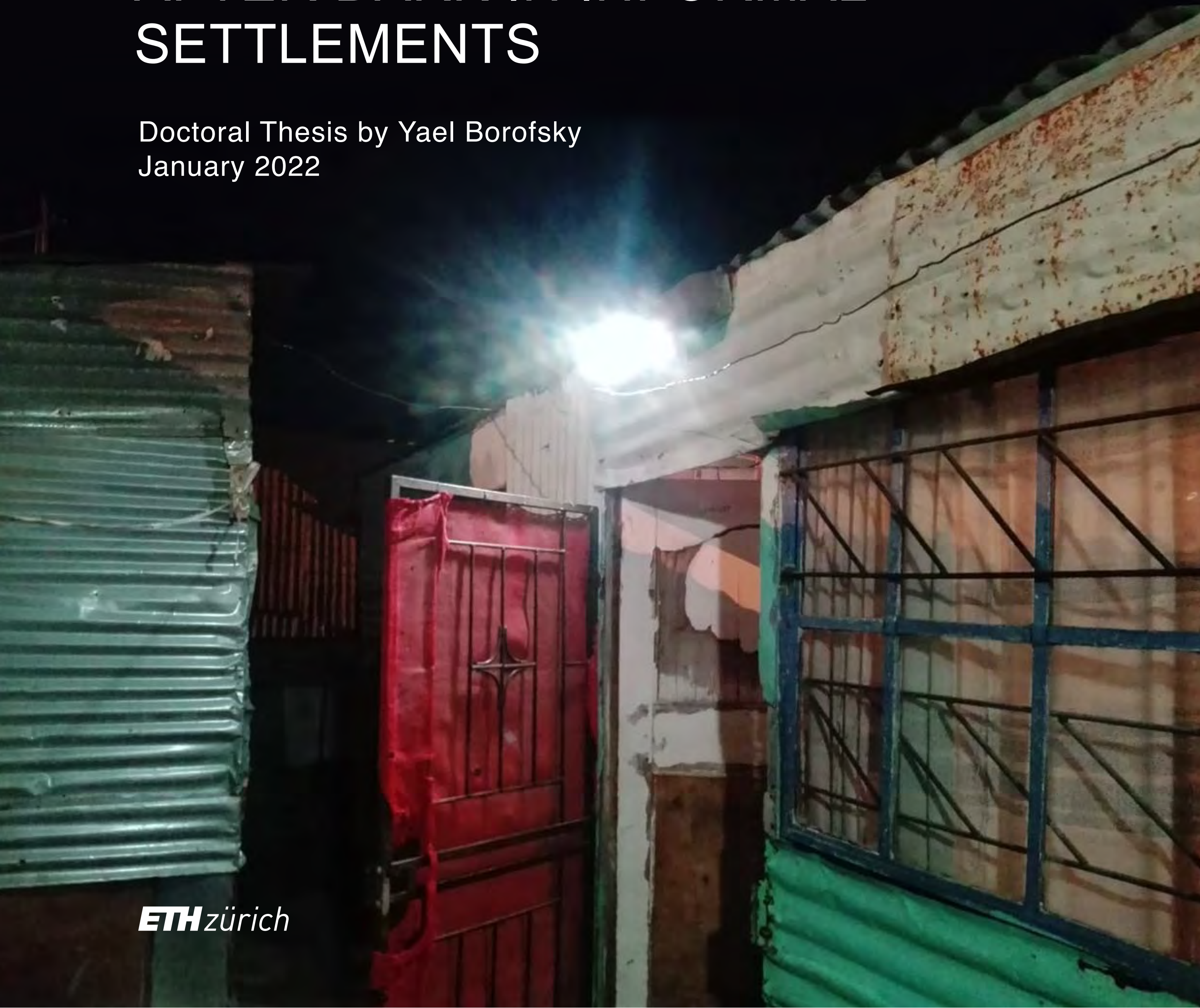

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Night in the Informal City: How Limited Public Infrastructure Shapes Life After Dark in Informal Settlements

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presented by

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SUMMARY

Informal settlements, and the share of urban residents living in them, are growing alongside rapid urbanization such that roughly one in seven people worldwide live in one of these neighborhoods. These numbers imply that a large share of urban dwellers live without the foundational elements of urban life that are necessary for health and prosperity. In studying informal settlement upgrading interventions, development economists have focused primarily on housing, water, and sanitation, yet this body of research has ignored an important aspect of life in informal settlements: nighttime. Compounded by little or no public lighting, the density, environmental vulnerability, shared water and sanitation infrastructure, not to mention high crime, make life at night in informal settlements difficult and dangerous.

To address this research gap and in order to better understand how access to public space and shared infrastructure in informal settlements is altered by darkness, this thesis focuses on two research questions in the context of one informal settlement in Cape Town, South Africa. The first two articles in this thesis address the question: What is the experience of pedestrian life at night in informal settlements and how applicable is the existing literature, given that it is mainly based on pedestrian activity in formal, high-income contexts? In both articles, I approach this research question from a quantitative perspective, by measuring nighttime pedestrian activity in the informal route network using proximity-infrared pedestrian motion sensors.

In the first article (co-authored), we test whether two urban planning theories intended to predict the most frequently used routes based on the configuration of the route network — route optimization and space syntax — correlate with the sensor data. First, we show that sensor-measured activity patterns in the early morning and evening in the informal settlement are quite different from each other, which may have to do with the different types of activities taking place at these times of day. Second, we find that the shortest path heuristic from route optimization theory is correlated with average pedestrian activity during the evening (6:00 – 9:00 pm), as well as on weekdays and weekends, but not during early morning hours (5:00 – 8:00 am). On the other hand, we find that the space syntax measure of choice does not perform well. The performance of both theoretical predictions varies by time of day, opening up questions about how pedestrian activity in informal settlements over the course of day differs from activity in formal areas.

In the second article (co-authored), we study how the lockdown of public life in South Africa in response to the COVID-19 pandemic affected mobility in the informal settlement in the evenings, early mornings, and at night from February to June 2020. We find that mobility was already decreasing in March prior to the first lockdown. We observe the biggest changes on weekends, key leisure times, and during typical commute hours (6:00 – 9:00 pm and 6:00 – 8:00 am), even though these time periods continue to have the highest activity, indicating that some people continued to commute. The mobility reduction we document is large, but gener-

ally smaller than reductions observed in high-income countries. Despite concerns that residents of informal settlements would not be able to comply with lockdown measures due to the constraints of life in these neighborhoods, we show that residents do comply to the best of their ability. We also show that awareness of COVID-19, prior to the lockdown, led to mobility declines. This article demonstrates the usefulness of pedestrian motion sensors to both the development economics and public health literatures.

The second two articles explore the experience of life at night through the lens of public lighting, asking how public lighting impacts the experience of nighttime life in informal settlements. In the third article, I assess the existing public lighting —high-mast lights — in the Cape Town informal settlement I study and show that the two high-mast lights installed on the periphery of the neighborhood produce low light levels that are not uniformly distributed. Combining the light measurements with household survey data, I then analyze how this poor lighting situation influences perceptions of safety, perceived crime risk, and willingness to engage in public space at night. I find that there is only a relationship between light levels and perception of safety on the brightest paths (10 lux or greater), but find no relationship between light levels and perceived crime risk or nighttime activities. Furthermore, I find that using distance from the nearest high-mast light as a proxy for the light measurements leads to mostly similar results, indicating that distance from the nearest high-mast light could be a proxy when studying large number of informal settlements. I show that high-mast lighting for informal settlements may not be sufficient to actually provide effective lighting at night, particularly since residents need light to access shared sanitation infrastructure.

The fourth article (co-authored) evaluates the results of a cluster-randomized controlled trial testing the efficacy and impact of an alternative type of public lighting — wall-mounted solar public lights. We show that the lights lead to a six- to eight-fold increase in light brightness and that residents living on treated paths report feeling safer, especially at night. On the other hand, we show this increased safety does not lead to widespread behavior change at night. We find that residents in both experimental groups are more likely to report using shared sanitation compared to baseline, an indication of spillover, but find no effect or a decrease for other activities, indicating spillover is not widespread. We find no effects on experience of crime. To my knowledge, this study is the first to test the impact of public lighting in an informal settlement and only the second randomized controlled trial studying the impact of public lighting.

This dissertation demonstrates that focusing on life at night in informal settlements has important implications for how academics across multiple disciplines as well as policymakers think about access to critical public infrastructure in these neighborhoods, not to mention basic quality of life and human dignity. Furthermore, this research explores the advantages and disadvantages of transdisciplinarity in randomized controlled trials and demonstrates how such an approach can lead to evidence-based recommendations informed directly by residents who intimately understand the experience of life at night in an informal settlement.

ZUSAMMENFASSUNG

Parallel zum Trend der raschen Urbanisierung wachsen auch die Ausmaße informeller urbaner Siedlungen sowie der Anteil jener Stadtbewohner, die in ihnen leben, stetig an. In etwa jeder siebte Mensch weltweit lebt heute in einer solchen Siedlung. Diese Zahlen lassen darauf schließen, dass ein Großteil der globalen Stadtbevölkerung keinen Zugang zu grundlegenden Elementen des städtischen Lebens hat, welche für Gesundheit und Wohlstand notwendig sind. Bei der Untersuchung von Maßnahmen zur Aufwertung informeller Siedlungen haben sich Entwicklungsökonomen in erster Linie auf die Kernbereiche Wohnen, Wasser und Sanitär konzentriert. Dabei wurde jedoch ein wichtiger Aspekt des Alltags in informellen Siedlungen außer Acht gelassen: die Nacht. Die dichte Besiedelung, die Anfälligkeit für Umweltschäden, die gemeinsame Nutzung der Wasser- und Abwasserinfrastruktur und nicht zuletzt die hohe Kriminalität machen das nächtliche Leben in informellen Siedlungen schwieriger und gefährlicher, zumal es keine oder nur wenig öffentliche Beleuchtung gibt.

Um diese Forschungslücke zu schließen und besser zu verstehen, wie der Zugang zum öffentlichen Raum und zur gemeinsamen Infrastruktur in informellen Siedlungen durch die Dunkelheit verändert wird, konzentriert sich diese Arbeit auf zwei Forschungsfragen im Kontext einer informellen Siedlung in Kapstadt, Südafrika. Die ersten beiden Artikel in dieser Arbeit befassen sich mit der folgenden Frage: Wie erleben Fußgänger das nächtliche Leben in informellen Siedlungen aus und inwieweit lassen sich die Erkenntnisse in der vorhandenen Literatur, die sich hauptsächlich auf Fußgängeraktivitäten in formellen, einkommensstarken Siedlungsgebieten bezieht, auf diesen Kontext übertragen? In beiden Artikeln bediene ich mich einer quantitativen Perspektive, um diese Forschungsfrage zu beantworten. Hierzu messe ich die nächtliche Fußgängeraktivität im informellen Wegenetz mithilfe von Infrarot-Bewegungssensoren.

Im ersten Artikel (als Co-Autorin mitverfasst) testen wir, ob zwei Theorien aus dem Bereich der Stadtplanung (Routenoptimierung und Space Syntax), die darauf ausgelegt sind, die meistgenutzten Routen auf Grundlage der Konfiguration des Wegenetzes zu prognostizieren, mit unseren Sensordaten korrelieren. Erstens zeigen wir, dass die mit den Sensoren gemessenen Aktivitätsmuster früh morgens und am Abend in der informellen Siedlung recht unterschiedlich voneinander sind, was auf die verschiedenen Arten von Aktivitäten zurückzuführen sein könnte, die zu diesen Tagezeiten stattfinden. Zweitens stellen wir fest, dass die Heuristik des kürzesten Weges aus der Theorie der Routenoptimierung mit der durchschnittlichen Fußgängeraktivität in den Abendstunden (18:00 – 21:00 Uhr) sowie an Wochentagen und Wochenenden korreliert, nicht aber in den frühen Morgenstunden (5:00 – 8:00 Uhr). Andererseits stellen wir auch fest, dass das bevorzugte Maß der Space Syntax sich nicht mit unseren Messungen vereinbaren lässt. Die Aussagekraft der beiden theoretischen Modelle variiert je nach Tageszeit, was Fragen darüber aufwirft, wie sich

die Fußgängeraktivität in informellen Siedlungen im Laufe des Tages von jener in formellen Gebieten unterscheidet.

Im zweiten Artikel (als Co-Autorin mitverfasst) untersuchen wir, wie sich die COVID-19-bedingten Einschränkungen des öffentlichen Lebens in Südafrika auf die Mobilität früh morgens, abends und nachts von Februar bis Juni 2020 innerhalb der informellen Siedlung ausgewirkt haben. Wir stellen fest, dass die Mobilität bereits im März, also vor dem ersten Lockdown, abgenommen hat. Die größten Veränderungen sind an Wochenenden, in der Freizeit und während der typischen Pendlerzeiten (18:00 – 21:00 Uhr und 6:00 – 8:00 Uhr) zu beobachten, obwohl in diesen Zeiträumen weiterhin die höchste Aktivität herrscht. Das deutet darauf hin, dass einige Menschen trotz der Maßnahmen pendelten. Der von uns dokumentierte Mobilitätsrückgang ist groß, aber im Allgemeinen geringer als in Ländern mit höheren Einkommensniveaus. Entgegen der Annahme, dass die Bewohner informeller Siedlungen auf Grund ihrer Lebensumstände nicht in der Lage seien, sich an einen Lockdown zu halten, zeigen wir, dass sie sich so gut wie möglich daran halten. Unsere Ergebnisse zeigen außerdem, dass schon vor Einführung des Lockdowns allein das Bekanntwerden von COVID-19 zu einem Rückgang der Mobilität führte. Anhand dieser neuen Erkenntnisse zeigt dieser Artikel die Nützlichkeit von Fußgängerbewegungssensoren für die Forschung, sowohl in der Entwicklungsökonomie als auch zu öffentlicher Gesundheit, auf.

In den weiteren beiden Artikeln wird die Frage gestellt, wie sich öffentliche Beleuchtung auf die subjektive Erfahrung des nächtlichen Lebens in informellen Siedlungen auswirkt. Im dritten Artikel bewerte ich die bestehende Straßenbeleuchtung — Hochmastleuchten — in der von mir untersuchten informellen Siedlung in Kapstadt und zeige, dass die beiden am Rande der Siedlung installierten Hochmastleuchten nur relativ niedrige Lichtpegel erzeugen, die nicht gleichmäßig verteilt sind. Ich kombiniere die Lichtmessungen mit Daten aus Haushaltsbefragungen und analysiere in Folge, wie diese schlechte Beleuchtungssituation das Sicherheitsempfinden, das wahrgenommene Kriminalitätsrisiko und die Bereitschaft, sich nachts im öffentlichen Raum zu bewegen, beeinflusst. Ein Zusammenhang zwischen Beleuchtungsstärke und Sicherheitsempfinden konnte dabei nur für die hellsten Wege (10 Lux oder mehr) festgestellt werden. Zusammenhänge zwischen der Beleuchtungsstärke und dem wahrgenommenen Kriminalitätsrisiko oder nächtlichen Aktivitäten konnten hingegen nicht nachgewiesen werden. Darüber hinaus zeigt sich, dass die Verwendung der Entfernung zur nächstgelegenen Hochmastleuchte als Proxy für die Lichtmessungen zu größenteils ähnlichen Ergebnissen führt, was darauf hindeutet, dass die Entfernung zur nächstgelegenen Hochmastleuchte als Proxy verwendet werden könnte, wenn eine große Anzahl informeller Siedlungen untersucht wird. Gemeinsam lassen diese Ergebnisse die Schlussfolgerung zu, dass eine Hochmastbeleuchtung für informelle Siedlungen möglicherweise nicht ausreichend ist, um tatsächlich eine effektive Beleuchtung in der Nacht zu bieten — insbesondere da Licht benötigt wird, um Zugang zu der gemeinsamen sanitären Infrastruktur zu gewährleisten.

Der vierte Artikel (als Co-Autorin mitverfasst) wertet die Ergebnisse einer Cluster-randomisierten kontrollierten Studie aus. In dieser Studie wurde die Wirksamkeit von an der Wand montierten Solarleuchten als alternative Art der öffentlichen Beleuchtung getestet. Wir zeigen, dass die Leuchten zu einer sechs- bis achtfachen Erhöhung der Helligkeit führen und dass die Anwohner der beleuchteten Wege angeben, sich insbesondere nachts sicherer zu fühlen. Andererseits zeigen wir auch, dass diese erhöhte Sicherheitswahrnehmung nicht zu einer weit verbreiteten Verhaltensänderung bei Nacht führt. Wir stellen fest, dass Anwohner in beiden Versuchsgruppen im Vergleich zur Ausgangslage häufiger angeben, gemeinsame Sanitäranlangen zu benutzen, was auf einen Spillover-Effekt hindeutet. Ob solche Effekte weiterverbreitet sein könnten, ist allerdings fraglich, da wir keine Veränderungen bezüglich anderer Aktivitäten feststellen konnten. Des Weiteren konnten wir keine Auswirkungen auf das Empfinden bezüglich der Kriminalität nachweisen. Diese Studie ist meines Wissens die erste, die die Auswirkungen der öffentlichen Beleuchtung in einer informellen Siedlung untersucht, und erst die zweite randomisierte kontrollierte Studie zur Untersuchung der Auswirkungen von öffentlicher Beleuchtung.

Diese Dissertation zeigt, dass ein stärkerer Fokus auf das nächtliche Leben in informellen Siedlungen wichtige Auswirkungen darauf hat, wie Wissenschaftler verschiedener Disziplinen und politische Entscheidungsträger über den Zugang zu kritischer öffentlicher Infrastruktur, sowie grundlegende Lebensqualität und Menschenwürde denken. Darüber hinaus beleuchtet dieses Forschungsprojekt die Vor- und Nachteile der Transdisziplinarität in randomisierten kontrollierten Studien und zeigt auf, wie ein solcher Ansatz zu evidenzbasierten Empfehlungen führen kann, die direkt von den betroffenen Bewohnern und ihrer eigenen Lebenserfahrung in einer informellen Siedlung bei Nacht stammen.

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LIST OF ABBREVIATIONS

SDG – Sustainable Development Goal

SSA – sub-Saharan Africa

RCT – Randomized controlled trial

NYC – New York City

ISTP – ETH Zurich Institute for Science, Technology, and Policy

DEC – ETH Zurich Development Economics Group

URI – Urban Research Incubator

NGO – Non-governmental organization

VPUU – Violence Prevention through Urban Upgrading

GPS – Global Positioning System

PIR – Proximity infrared

UCL – University College London

WHO – World Health Organization

SI – Oxford University's Coronavirus Government Response Stringency Index

PV – Photovoltaic

DST – Daylight Savings Time

CPTED – Crime Prevention through Environmental Design

SJC – Social Justice Coalition

ZAR – South African Rand

EPWP – South African Expanded Public Works Programme

ITT – Intention to Treat Effect

IV – Instrumental Variables

LATE – Local Average Treatment Effect

WTP – Willingness to Pay

SDI – Slum Dwellers International

INTRODUCTION

Informal settlements are urban spaces that are defined by what they lack: tenure security, government recognition, durable housing, space, and access to adequate public infrastructure (United Nations, 2020). Yet, informal settlements, also called slums, and the share of urban residents living in these neighborhoods, are growing alongside rapid urbanization, especially in sub-Saharan African, South and Southeast Asia, and Latin America. UN Habitat estimates that approximately one billion people (or one in seven) worldwide live in these areas (United Nations, 2020).

These numbers imply that a large share of urban dwellers live without the foundational elements of urban life that are necessary for health and prosperity. Although rapid urbanization has been considered the primary way many rural people have risen out of poverty, to the extent that those rural-urban migrants wind up living in informal settlements, new types of deprivation may be simultaneously on the rise (Bryan et al., 2020; Garau et al., 2005; Gulyani & Bassett, 2010). Addressing the various deprivations that exist in informal settlements worldwide has been a focus of the international community since at least the 1970's, when informal settlement or slum removal lost traction and the idea of improving informal settlements, in various ways, took hold (Owens et al., 2018). While progress has been made in some areas, particularly in Latin America, there is no consistent approach or playbook to improving quality of life in informal settlements (Brown-Luthango et al., 2017). Meanwhile, international organizations like UN Habitat point out that informal settlements are expanding faster than deprivations can be addressed (UN-Habitat, 2011).

In studying informal settlement improvement interventions, development economics researchers have primarily focused on housing (e.g., Galiani et al., 2018; Strassmann, 1984), water and sanitation (e.g., Devoto et al., 2012; Günther and Horst, 2014), and street pavement (Gonzalez-Navarro & Quintana-Domeque, 2012). Yet, this body of research has ignored an important aspect of life in informal settlements that has implications for urban infrastructure: nighttime. Life in informal settlements cannot possibly be easy at night. Dense, irregular path networks, poor sewage maintenance or flooding, shared water and sanitation infrastructure, not to mention high vulnerability to crime (Brown-Luthango et al., 2017), create a situation that is highly unpleasant and potentially dangerous, but nearly impossible to avoid. These problems are compounded by little or no public lighting, hindering access to infrastructure and economic opportunities at night.

These issues raise an important question about the progress that has been made with respect to access to infrastructure in informal settlements over the last half a century or so: how does access to public space and shared infrastructure in informal settlements change once it gets dark out? Given the limited research in development economics, this thesis proceeds from this broad question to quantitatively explore the dynamics of life at night in informal settlements, while drawing on knowledge developed in urban studies and planning, criminology, and engineering.

First, rather than starting from a narrative defined by what is lacking, the first half of this dissertation explores pedestrian activity at night in an informal settlement in Cape Town, South Africa. Very little research exists on pedestrian activity in informal settlements and almost none on nighttime activity, despite the fact that so much of the literature in various fields is concerned with both the accessibility of infrastructure and high crime, two topics which are linked to pedestrian behavior at night in informal settlements. The absence of information about the dynamics of human movement in informal neighborhoods took on new importance as COVID-19 spread around the globe in 2020 and concerns about the feasibility of social distancing in informal settlements gained global attention. Yet, this topic is also policy relevant outside the context of COVID-19 — knowing which parts of settlements are used most and understanding activity patterns over the course of the night could facilitate better decisions about the siting and distribution of shared infrastructure and services, as well as crime prevention strategies.

The second half of this thesis explores the experience of life at night through the lens of public lighting in the same Cape Town-based informal settlement. Streetlighting is a public service in and of itself, though it is frequently absent or limited in informal settlements, but it is also an enabler of access to other services. No comprehensive data exist on the availability of public lighting in informal settlements worldwide. Although the impact of public lighting on various aspects of life at night will be explored in this thesis, it is already known that public lighting enables visibility when it is dark out, therefore removing at least one barrier to accessing shared infrastructure, like toilets, economic activities, as well as social activities at night. Understanding the role it can play in life at night stands to change how international organizations and local city governments, which are concerned with safety and security (Mboup, 2013; UN-Habitat, 2011), think about access to services in informal settlements. Sustainable Development Goal (SDG) 11 is to "make cities and human settlements inclusive, safe, resilient and sustainable," focusing in particular on affordable housing, public transport, municipal waste management, air pollution, and public space, however, not one target or indicator addresses the threat to inclusivity, safety, resilience, and sustainability that an insecure nighttime life represents for achieving this goal (United Nations, 2021).

The rest of this introductory chapter is organized into the following five sections. The next two section describe the research gaps in the literature on infrastructure in informal settlements and the experience of life at night, which are the two main motivators of this thesis. The third section explains the research approach, the study site, and the institutional context for the dissertation. In the fourth section, I summarize the findings from each of the four articles. Finally, I describe my contribution to each article.

THE INFORMAL BUILT ENVIRONMENT AND PEDESTRIAN ACTIVITY

Pedestrian activity in the urban built environment is a central topic in the study of cities because the flow of people and the places they choose to walk have important consequences for the placement of urban services, for economic activity, for public health, and for safety and security. While pedestrian flows are not a focus of research in development economics, the topic touches a wide range of other literatures, from theories on pedestrian route choice (e.g., Bongiorno et al., 2021; Hillier and Iida, 2005; Willis et al., 2004), to the walkability of particular streets (e.g., Salazar Miranda et al., 2021), to crime hot spots and crime displacement (e.g., Chalfin et al., 2020; Weisburd et al., 2012), to the use of urban public spaces (e.g., Gehl, 1989) not to mention the design of various pedestrian detection algorithms and technologies (e.g., Fujisawa and Hasegawa, 2012; Salazar Miranda et al., 2021; Uttley and Fotios, 2017).

Yet, very little of any of these literatures focus on pedestrian life in low-income countries and even fewer studies focus on informal settlements. In 2013, UN Habitat dedicated an entire report to streets as key drivers of urban prosperity in rapidly urbanizing cities in low- and middle-income countries (Mboup, 2013). Perhaps that is why mobility, with a focus on access to transportation, has been included as a target in SDG 11 (United Nations, 2021). Yet, lessons about pedestrian activity from predominantly high-income, western countries may not be relevant in rapidly urbanizing cities, particularly in sub-Saharan Africa (SSA) and South Asia, where the issues pedestrians face and even the motivations for walking may differ (Anciaes et al., 2017).

Research on pedestrian behavior in high-income urban areas is likely to be difficult to transfer to informal settlements in low- and middle-income countries for several reasons. First, path networks in most informal settlements are unplanned and they are not static, meaning not only can the width and quality of paths vary, but they can also change entirely or disappear completely from day to day if a resident decides to build a structure or block a path. Second, the nature of activity taking place in paths can vary greatly in comparison to formal city streets. Activities, like going to the toilet or collecting water, which typically occur in private homes in formal areas require residents of informal settlements to enter public space (or find a way to avoid it). In addition, the small size of houses and limited private outdoor space, means doing laundry, social activities, and even the storage of personal items can all take space in informal paths (Cutini et al., 2019; Kamalipour, 2020), influencing the pedestrian experience. Third, the density and irregularity of informal settlements not only means that few cars can pass through most paths, but it can make navigation through the settlement difficult and limit opportunities for egress, potentially altering the way pedestrian think about and use the space. Furthermore, informal settlements frequently exist like islands or on the periphery of formal urban networks, limiting connectivity between the internal path network and the broader city and limiting who uses informal urban spaces (Karimi & Parham, 2012).

Those studies that are conducted in lower-income cities typically focus less on pedestrian behavior within settlements and more on the mobility options that connect informal neighborhoods to the formal city (Anciaes et al., 2017; Hidayati et al., 2020; Hillier et al., 2000; Mohamed, 2016). One study on how to address high pedestrian fatality rates in South Africa specifically acknowledges that the research does not include informal settlements, although they acknowledge that informal settlements may have unique vulnerabilities with regard to pedestrian safety (Albers et al., 2010). Only one study, to my knowledge, analyzes pedestrian activity in an informal settlement during evening hours, from 6:00 – 8:00 pm (Mohamed, 2016).

One possible reason why so little research exists, is that so few informal settlements are mapped (Kamalipour & Dovey, 2019). Another reason may be the difficulty and, sometimes, danger of measuring pedestrian behavior in informal settlements. Yet, a better understanding of how pedestrians use informal settlements, particularly at night, stands to enrich the way development actors think about solving problems within informal settlements, such as providing services, resolving disputes, or improving economic opportunities. Inspired by this research gap, Article 1 uses highly granular data gathered from pedestrian motion sensors developed for this thesis to study pedestrian activity at night in one informal settlement in Cape Town. In addition, my co-authors and I test whether two existing theories of pedestrian route choice developed in high-income cities predict the pedestrian path usage measured by the sensors. By using pedestrian motion sensors to gather this novel dataset, it is possible to study pedestrian behavior in many paths throughout a single neighborhood without field staff incurring the risk of working late at night. Article 2 also draws on the pedestrian motion data, but in this case, explores how nighttime pedestrian activity in an informal settlement changes in response to the first COVID-19 lockdown. Since the sensors were already passively collecting data at the onset of the pandemic, it is possible to descriptively compare changes in average motion before and after the initial lockdown, as well as subsequent adjustments to the regulations, however, causal inference is not possible.

PUBLIC LIGHTING AND ITS ROLE IN INFORMAL URBAN SPACES

The fundamental challenge of nighttime is that humans cannot see well in the dark. The need to correct for this weakness takes up so much mental space that it invades our language, birthing common figurative phrases like, “to shed light on” or “to illuminate” or “to shine a light” when talking about ideas or actions totally unrelated to the presence or absence of actual light. The banality of these sayings speaks to the value humans place on light. With that in mind, it is surprising that public lighting in informal settlements has not gained more attention from researchers studying infrastructure access in informal settlements or been included as one of the many targets under SDG 11 (United Nations General Assembly, 2020).

To my knowledge, only a few other studies look at the role of public lighting in informal settlements (Briers, 2021; Kretzer, 2020; Kretzer & Walczak, 2020). To be clear, the issue is not that all informal settlements lack public lighting. To the contrary, some large-scale upgrading projects in the 1990s and early 2000s included streetlighting as part of the suite of infrastructure services provided to informal settlements (UN-Habitat, 2011). In South Africa, many informal settlements are lit with high-mast lights, 30 to 40-meter-tall flood lights, which are more typically used to light parking lots or stadiums, rather than residential areas. Other countries in sub-Saharan Africa, such as Kenya and Namibia, have followed this example, installing high-mast lights in informal settlements in Nairobi and Windhoek (Ikela, 2020; Musoi et al., 2014). In India, news reports tout the installation of streetlights in scattered informal settlements (Kulkarni, 2014; Venkat, 2016) and Auerbach (2020) finds streetlights are reasonably common in informal settlements in Bhopal and Jaipur. In Colombia, the government provides streetlighting to recognized informal settlements, but for those neighborhoods that have not gone through a formalization process, residents often build their own streetlighting (Kretzer, 2021). Yet, the vast majority of the research does not quantitatively study the efficacy or impact of public lighting in communities that have received streetlights.

The consequences of darkness in informal settlement are numerous. Without light it is difficult to navigate narrow paths and detect obstacles, such as stones or pooled water. It is also more difficult to recognize faces, or to navigate to shared water and sanitation infrastructure. Furthermore, the absence of light in informal settlements can limit social and economic activity (Boyce, 2019). Darkness is also heavily associated with fear, which can inhibit people's behavior and harm their quality of life.

The vast majority of research on public lighting and its impacts on the experience of life at night has been conducted in high-income cities, largely in the UK, the US, and Europe. The findings from this body of work suggests that public lighting does ameliorate many of the difficulties of darkness by improving obstacle detection (Boyce, 2019; Fotios & Cheal, 2009; S. Fotios & Uttley, 2018) and making it easier to recognize other people's faces (Fotios, Yang, et al., 2015). In addition, many studies find that lighting increases feelings of safety at night (Atkins et al., 1991; Blöbaum & Hunecke, 2005; Boyce et al., 2000; Kaplan, 2019; Kaplan & Chalfin, 2020; Nair et al., 1997; Nasar & Jones, 1997; Peña-García et al., 2015; Svechkina et al., 2020; Vrij & Winkel, 1991; Wu & Kim, 2018), increases confidence walking alone at night (Fotios, Unwin, et al., 2015; Nasar & Bokharaei, 2017a), and can reduce crime (Chalfin et al., 2021; Doleac & Sanders, 2015; Domínguez & Asahi, 2019; Kaplan & Chalfin, 2021; Welsh & Farrington, 2008).

While many of these effects seem obvious, it has proven extraordinarily difficult to quantitatively document the effect of light on life at night because randomizing lighting installation in order to rigorously measure effects is not easy. Many of these studies have been criticized for small samples sizes, lack of a control group, or unrealistic experimental scenarios (e.g., on a college campus or in a lab). Some studies on the impact of public lighting on crime have tried to work around this by using daylight savings time (Doleac & Sanders, 2015; Domínguez & Asahi, 2019), streetlight outages (Chalfin et al., 2020), and moonlight (Kaplan, 2019; Schafer et al., 2010; Stolzenberg et al., 2017) to generate sufficient variation to estimate the effect of light on crime, as well as pedestrian activity (Uttley & Fotios, 2017).

Only one randomized controlled trial (RCT) studying the impact of public lighting exists (Chalfin et al., 2021). This study focused on the crime reduction effects of temporary public lighting installation in New York City's (NYC) public housing projects, finding that public lights reduce nighttime outdoor crime by 35%. The study does not, however, report effects on other aspects of nighttime life, such as perceptions of safety or nighttime activities. Furthermore, while this research also focuses on a low-income urban population, there are many differences between a New York City public housing project and an informal settlement. Informal settlements are sprawling, unplanned neighborhoods with communal infrastructure, while public housing projects are government-run apartment buildings in which tenants have access to private water and sanitation. In the NYC study, the public lighting intervention brightened up the common area around the building(s), mainly used by residents either accessing or exiting their building or socializing, rather than used by pedestrians for through-traffic. While the activity in informal settlements may also be dominated by residents, the areas that need lighting are not just public gathering spaces, but the narrow paths that people use to get from point A to point B. Therefore, while this study is extremely useful in demonstrating the feasibility of a public lighting field experiment and important for the fields of criminology and urban planning, the focus is not broad enough to answer many questions about the benefits of light that are important for informal settlements and it is unclear that the results on crime reduction are transferrable to such a different context.

Articles 3 and 4 both address the research gaps outlined here by drawing on data gathered from the first randomized field experiment testing the impact of solar public lighting in informal settlements. It is only the second randomized controlled trial to test the impact of public light on life at night. Article 3 uses light measurements and household survey data gathered prior to the implementation of the lighting intervention to understand the impact of the existing public lighting situation on perception of safety, perception of crime risk, and nighttime activities in an informal settlement. Article 4 evaluates the impact of the solar public lighting intervention, by assessing the efficacy of solar public lighting and estimating the impact of additional public lighting on perception of safety, perception of risk of crime, nighttime activities, as well as experience of crime in the same informal settlement. By randomizing the lighting intervention, it is possible to isolate the causal effect of lighting on important aspects of nighttime life.

RESEARCH APPROACH AND MAIN FINDINGS

Given the gaps in the literature, particularly in the field of development economics, and inspired by the overarching question about life at night informal settlements, this thesis contends with two research questions.

The first is: *What is the experience of pedestrian life at night in informal settlements and how applicable are prevailing concepts of pedestrian activity developed in formal, high-income contexts?*

I approach this research question from a quantitative perspective, seeking to measure and describe actual pedestrian activity (or motion) in the informal route network on average, by time of the day, and day of the week. Using proximity-infrared pedestrian motion sensors co-developed with Sensen, a company dedicated to building dataloggers for international development projects, it was possible to measure pedestrian activity in one informal settlement in Cape Town from October 2019 until June 2020. Due to the limitations of the sensor technology, activity could not be accurately measured during peak daylight hours, so the dataset is limited to the hours between 6:00 pm – 8:00 am. While pedestrian detection using sensors is common in many formal cities throughout the world, to my knowledge, this is the first time this data collection approach has ever been tried in an informal settlement. The first two articles in this thesis draw on the pedestrian motion sensor data to study nighttime pedestrian activity, but with two very different questions in mind. In Article 1, my co-authors and I use data from the first two months of the study period to understand the basic dynamics of nighttime pedestrian activity and to test whether two theories intended to predict pedestrian activity, which have primarily been developed based studies in high-income cities, correlate with the sensor data.

The second article came about in response to the COVID-19 pandemic. When COVID-19 began rapidly spreading across the globe, the pedestrian motion sensors were already installed. As lockdowns went into force worldwide, many thought leaders from academia and the international development community were concerned that social distancing measures, economic shutdowns, and other regulations designed to limit the spread of COVID-19 would be impossible to follow for residents living in informal settlements, who live in close quarters, share basic hygiene services, cannot work from home, and often do not have the financial capacity to go without work. Meanwhile, many of the sensors were still passively collecting data. Using data collected between February and June 2020, it was possible to approach the overarching question about pedestrian activity from a public health perspective, by analyzing the extent to which residents appeared to be complying with the lockdown restrictions, including nighttime curfews.

The second question is: *Does improved public lighting impact the experience of nighttime life in informal settlements?*

I approach this research question from two angles in the third and fourth articles. In the third article, I approach it from the technology assessment perspective, where I measure the existing lighting situation in an informal settlement and evaluate the effectiveness of the existing public lighting in an informal settlement. Since there are no lighting standards for informal settlements, I use lighting standards for formal areas in the City of Cape Town as the nearest possible point of reference. In addition, I analyze how the existing lighting links to residents' perceptions of safety, risk of crime, and engagement in public space at night.

The fourth article reports the results of an RCT to evaluate the efficacy and viability of an alternative to the existing public lighting and assess how this alternative impacts the same aspects of nighttime life studied in the third article as well as experience of crime. Using this approach, it is possible to go beyond description of light and nighttime experience, to estimate the causal impact of light on those randomly selected to receive the alternative public lighting intervention.

STUDY SITE: AN INFORMAL SETTLEMENT IN CAPE TOWN, SOUTH AFRICA

While informal settlements exist all over the world, I address both main research questions by focusing on one informal settlement in Cape Town, South Africa. Compared to many of its sub-Saharan African neighbors, South Africa is often seen as an outlier. According to the World Bank's World Development Indicators, in 2020 about 77% of urban residents had access to at least basic sanitation, compared to about 47% in sub-Saharan Africa overall. Similarly, in 2019 nearly 88% of urban residents had electricity access, compared to 78% in all of SSA. And, when it comes to informal settlements, about 26% of the South African urban population lives in one, compared to nearly 54% in SSA overall. These relative levels of urban development, however, do not tell the whole story. South Africa is the most unequal country in the world (Gini coefficient = 63 as of 2014) — more so than many of its neighbors despite its development advantages — indicating that its development shortcomings hit the lowest income people hardest (International Monetary Fund, 2020).

This divide could not be more immediately visible in Cape Town, where informal settlements collect near the international airport and line the N2 highway that leads to the city's downtown — an internationally renowned tourist hub. Despite the glamour and popularity of the tourist industry, nearly 14% of urban residents in Cape Town live in informal settlements (van der Westhuizen, 2017). In fact, the City of Cape Town has well over 400 informal settlements (Ndifuna et al., n.d.), many of them highly concentrated in areas that were previously zoned for Black African people under the apartheid regime's racially divided land use planning strategy (*Group Areas Act of 1950*, 1950). As a result, despite Cape Town's international reputation, its informal settlements represent the deep economic and racial divides that also characterize this seemingly highly developed, world-class tourist city, not to mention the country, more broadly. Therefore, although South Africa and Cape Town, specifically, may be seen as better off than many other rapidly urbanizing areas in sub-Saharan Africa, the people living in informal settlements are not necessarily benefitting from the overall progress. Furthermore, as the share of the global urban population is only predicted to further increase by 2050 (Dodman et al., 2018), along with absolute number of informal settlement dwellers alongside it, it is likely that many more of world's urban poor will be living in the kind of highly unequal urban environment that characterizes Cape Town, as well as several other cities including Bogotá and Rio de Janeiro, among others.

Against this backdrop, studying informal settlements, particularly the experience of night and the importance of public lighting, in Cape Town is instructive for a variety of reasons. First, although the City of Cape Town does not necessarily formally recognize informal settlements, they have a number of policies in places designed to provide some level of security to residents of informal settlements as well as public services, such as shared water and sanitation, even for informal settlements located on privately-owned land. Many informal settlements are also connected to the electric grid. Most relevant to this study, the City of Cape Town provides public lighting to many informal settlements. Most frequently, informal settlements are lit with high-mast lighting, though a small number of informal settlements have public lights mounted onto electricity distribution poles.

The existence of public lighting opened up an opportunity to study nighttime in an informal settlement under a pre-existing lighting technology regime, rather than selecting an informal settlement with a one-off pre-existing public lighting intervention or no light at all. In addition, since high-mast lighting is used all over South Africa as well as in other nearby countries (e.g., Kenya and Namibia) studying high-mast lighting in Cape Town makes it possible to evaluate an alternative that has relevance beyond the city limits.

Finally, there would undoubtedly be benefits to posing my research questions in a much larger number of neighborhoods, most notably in terms of external validity. Yet, given the limited academic understanding of the dynamics of nighttime life in informal settlements and the difficulty of entering these neighborhoods without prior relationships, focusing on one informal settlement made it possible to conduct both inter- and transdisciplinary research in a rigorous, but also participatory way.

INTERDISCIPLINARITY AND TRANSDISCIPLINARITY IN RANDOMIZED CONTROLLED TRIALS

This doctoral work emerged out of an interdisciplinary environment at the ETH Zurich Institute for Science, Technology, and Policy (ISTP) and the ETH Zurich Development Economics Group (DEC). As part of the ISTP's Urban Research Incubator (URI), I embraced the commitment to develop an interdisciplinary, transdisciplinary, and policy relevant doctoral research project. As a result, the broader project described in all four articles of this dissertation was developed as part of an interdisciplinary collaboration with ISTP URI and Department of Architecture PhD student Stephanie Briers. In addition, I benefitted from input and cooperation from ISTP colleagues in the fields of urban planning, criminology, and engineering as well as from DEC colleagues working in development economics and quantitative social science.

Transdisciplinary research goes beyond the realm of academic fields to, as Lang et al. (2012) describe it, "integrate the best available knowledge, reconcile values and preferences, as well as create ownership for problems and solution options."[1] While the benefits of interdisciplinarity are increasingly being appreciated in RCTs (Bamberger et al., 2016), incorporating a transdisciplinary approach to research, which emphasizes collaborative partnership with study participants, into a quantitative research project designed around an RCT has some important advantages and disadvantages. The main challenge to working in a transdisciplinary manner in the context of an RCT is that participants in the experiment cannot necessarily be fully knowledgeable of the primary goals of the study or give input on every aspect of the project in order to avoid bias linked to priming. While Arnstein (1969) was not writing directly about transdisciplinary research when she wrote her well-known article describing the ladder of citizen participation, her work informs the concept. By necessity, this experiment violated her tenet that participation implies that the "have-nots" — in this case, study participants — have "the real power needed to affect the outcome of the process."

In the context of this specific project, this limitation presented the following challenges. When the idea for the sensors was presented to the community, one important question that came up prior to the start of the baseline sensor data collection was what benefit the sensor project would provide to the community. Although one of the original intentions was that the sensors would be used in the RCT to measure the pedestrian response to the alternative public lighting intervention, this information could not be shared because learning about the lighting intervention during baseline data collection could lead to residents altering their behavior and therefore lead to biased data. That said, had the community been fully aware that the sensors were part of a broader public lighting project, they would have seen the sensors as linked to development and perhaps been more likely to protect them from damage or theft. In addition, since there is no RCT without randomization, residents had no control over who received a light in the intervention phase of the project and therefore no say in which areas would be lit and which areas would have to wait. Although it is entirely possible that residents would have opted for a random process to decide who would receive lights during the intervention phase and who would have to wait, this option was not provided, but rather the randomization was presented as the terms on which the implementation of the solar public lighting project was premised.

On other hand, the framework of transdisciplinarity brought many benefits to the RCT implementation. First, residents worked on nearly every aspect of the data collection, even working as enumerators during the two household surveys despite having no prior experience. While it is not common practice for development economists to hire enumerators from the sample of people they wish to study for fear of bias, in South Africa, where this project took place, it is

[1] The authors define transdisciplinary research as follows: "Transdisciplinarity is a reflexive, integrative, method-driven scientific principle aiming at the solution or transition of societal problems and concurrently of related scientific problems by differentiating and integrating knowledge from various scientific and societal bodies of knowledge" (Lang et al., 2012).

common practice because it helps build trust between the community and the researchers and provides much-needed employment opportunities. Furthermore, the leaders of the community controlled the majority of the hiring process, once it was clear approximately how many staff were needed and what the basic job description would be. By working with the leaders on staffing each phase of the project and having residents work on all aspects of data collection, from mapping to sensor data collection to light measurements to household surveys, the residents developed skills useful for future job applications, had the ability to create and absorb knowledge about the project. In turn, the research benefitted in several ways.

First, even though not all details of the project could be provided up front, having residents participate engendered trust with community members who did not directly interact with the researchers. Based on an understanding of this trust and their own experience living in the neighborhood, the leaders and local field staff provided input on how best to organize data collection processes to ensure safety or to pre-empt concerns the community might have about the data collection activities. For example, during the light measurements, the team collecting the data did not need to interact with anyone in order to do their job. Still, someone suggested it would be helpful for data collectors to announce their presence to each household they passed so that residents would not get scared by the noise of people standing around outside their house (which could also sound like someone preparing to commit a burglary).

Another important example of the value of a transdisciplinary approach comes from working with the pedestrian motion sensors. After the first few months of sensor data collection, in addition to a small number of thefts and vandalism, several of the sensors had malfunctioned for other reasons. While the three residents working as sensor data collectors had been trained to collect data from the sensors, they had not been trained to fix malfunctions, like replacing discharged batteries. In January 2020, one of the Sensen's engineers came to Cape Town to help fix the damaged sensors so that as many as possible would be working when the lighting intervention began. Over the course of the two weeks working with the data collectors on the sensor repairs, they shared a lot of observed knowledge how the sensors behaved in the field, they had identified locations that appeared to be particularly problematic for various reason, and often formed relationships with people living near the sensors so that they would receive reports if damage occurred. In addition, beyond the data collection, they expressed a strong interest in understanding how the sensors worked and wanted to learn to do minor repairs. As a result, the Sensen engineer and I organized a set of supplies and trained the team to open the sensors, troubleshoot the most common problems, and conduct minor repairs, such as charge and replace batteries. When the COVID-19 pandemic hit, the initiative and ownership over the project that data collectors demonstrated ultimately made it possible to collect the data for the second article. Without their close attention to the sensors and their willingness and ability to solve problems without any researchers on the ground, it is likely even more sensor data would have been lost and less would have been learned from this method. There are many other examples of how the project was improved by the process of close collaboration with the leadership and residents of this community. Most notably, at the conclusion of the project those who had been involved felt a sufficient level of ownership of the project beyond the researchers to develop a plan for continuing to maintain the lights that were installed as part of the RCT.

Beyond the project site, the transdisciplinary framework guided our efforts to engage with many other types of stakeholders, who contributed essential knowledge to the project with differing degrees of involvement. Through direct engagement with city officials across several departments about the problems with existing public lighting in informal settlements and the options for alternatives, my collaborator and I gained key insights into policy and regulatory challenges that limit technology options in informal settlements. Our project partner, the Social Justice Coalition, a local NGO focused on advocacy for informal settlements, also helped shape the project by providing insights from their public lighting campaign, shared useful correspondence between the organization and the city, while continuously highlighting their own ongoing questions about public lighting that could guide our work. Other Cape Town NGO's, such as Violence Prevention through Urban Upgrading (VPUU), shared their knowledge and experience conducting informal settlement enumerations, which allowed us to simultaneously collect baseline data and conduct an informal settlement enumeration (counting and documentation of all structures and people). They also invited us to present to their team to report back on what we learned and how we modified their approach. The practical outputs of the dissertation intended to inform policy that were guided by these interactions are discussed in greater detail in the Conclusion. Since many of these aspects of the collaboration inform the policy recommendations, but may not be directly discussed in the articles, it is important to acknowledge them here for future researchers seeking to understand how a transdisciplinary research approach can inform an RCT, even if it is not always possible to adhere to all aspects of the approach.

OVERVIEW OF THE FOUR ARTICLES

All four articles in this dissertation are based on data collected from the same solar public lighting project, conducted in an informal settlement in Cape Town. The first two articles address the first overarching research question, describing pedestrian activity in the informal settlement at night (prior to any intervention). The second two articles focus on understanding the role of public lighting in nighttime life in the informal settlement. All four also represent applied empirical research and while that work is informed by theory primarily from criminology and urban studies and planning, the focus of this dissertation is not on theory-building, but rather on developing a base of evidence on two understudied topics in the context of informal settlements.

ARTICLE 1:
PREDICTING PEDESTRIAN ACTIVITY IN INFORMAL SETTLEMENTS

Article 1 is co-authored with S. Briers, the other ISTP PhD student who collaborated on this project, and Prof. Isabel Günther. The article presents the first description, to my knowledge, of nighttime pedestrian activity in an informal settlement based on highly granular data collected over two months using pedestrian motion sensors. The inspiration for the use of pedestrian motion grew out of my surprise that no quantitative evidence exists to support the widely held intuition that pedestrian will choose to walk on lit streets over unlit streets. In addition, on our first visit to the informal settlement, the leaders pointed out that the area where the high-mast light is located is a crime hot spot. This anecdote raised questions about how pedestrians in the informal settlement choose where to walk. Furthermore, while doing the preliminary mapping of the informal settlement, I was surprised to learn from the leaders who collaborated with us, that residents rarely walk in areas of the neighborhood that are not near where they live, despite the fact that the neighborhood is relatively small. This led me to wonder whether residents only used certain paths and avoided others or whether path usage was relatively evenly distributed. These inspirations guided the development of the pedestrian motion sensors and the ultimate use of the data.

This article focuses not only on describing the activity patterns derived from the sensor data, but also on understanding whether existing theories that predict pedestrian route choice — route optimization and space syntax — are relevant in the context of informal settlements. In formal cities, urban planners commonly use various technologies to measure pedestrian activity to understand the demand on the built environment, however, prior to this study, this data collection approach had not previously been used in informal settlements. Route optimization and space syntax are two prevailing theories about pedestrian route choice that can be operationalized using a shortest paths analysis (route optimization) and a choice analysis (space syntax), respectively, to predict the most used paths, but they have predominantly been tested in formal cities. We measure and describe pedestrian activity in an informal settlement in Cape Town in the early morning and evening hours between October 1 – November 30, 2019. Since the sensors work by detecting body heat and gather no other information about who walks past the sensor, this article focuses purely on pedestrian activity, not mediated by any other factors that might influence who walks where at a given time. We test whether these two theories, both of which only account for characteristics of the path network, explain the sensor-measured pedestrian motion. We find that the shortest paths calculation (route optimization) is correlated with overall average pedestrian activity during the evenings (6:00 - 9:00 pm) as well as on weekdays and weekends, but there is no significant correlation during morning hours (5:00 – 8:00 am). Our findings further suggest that the space syntax choice measure intended to predict the most frequently used routes does not perform well in informal settlements. We also find that the performance of both theoretical calculations varies by time of day, opening up questions about how movement patterns in informal settlements over the course of the day may differ from those in formally planned neighborhoods.

ARTICLE 2:
MOBILITY IN INFORMAL SETTLEMENTS DURING A PUBLIC LOCKDOWN — A CASE STUDY IN SOUTH AFRICA

Article 2 is co-authored with Prof. I. Günther and has been submitted to PLOS ONE (status: Revise and Resubmit). The idea for this article came about in response to the COVID-19 pandemic. The conditions in informal settlements led many development economists, international development organizations, and public health officials to worry that complying with lockdowns would not be possible and that COVID-19 could easily spread. Making use of the fact that pedestrian motion sensors previously installed in an informal settlement were passively collecting data at the time that lockdowns of public life were imposed in South Africa, this paper descriptively analyzes the extent to which residents of informal settlements were able to comply with lockdown restrictions that required them to stay indoors, despite living in small spaces, needing to use shared infrastructure, and having little financial cushion to fall back on as the economy shut down. Although this article was not planned at the outset of the research, it demonstrates the usefulness of pedestrian motion sensor data in informal settlements to both research and policy across various fields.

Based on the pedestrian motion sensor data, we study how the lockdown affected mobility in the evenings, early mornings, and during the nights from February 14 - June 18, 2020. We find that mobility was already decreasing in March prior to the start of lockdown by 23% in paths — about half of the overall decline — and by 19% in shared courtyards, called compounds. We observe the biggest changes on weekends, normally key leisure times, and between 6:00 - 9:00 pm as well as between 6:00 - 8:00 am, spanning typical commute hours. That said, we still observe the most activity during these hours of the day, indicating that some people continued to commute. The results indicate that mobility reduction is large, though generally smaller than reductions observed in high-income countries. We find that residents of informal settlements comply with state-mandated lockdowns to the best of their ability given the circumstances, but that awareness of COVID-19 prior to the implementation of strict lockdowns also led to mobility declines.

ARTICLE 3:
NOT ALL LIGHT IS RIGHT — A STUDY OF LIGHT LEVELS AND LIFE AT NIGHT IN A CAPE TOWN INFORMAL SETTLEMENT

Article 3 is a single-authored paper that serves as both an assessment of the existing high-mast lighting in the informal settlement as well as an empirical analysis of how that lighting influences the experience of life at night. Using the baseline data collected for the RCT, the article evaluates the public lighting provided by high-mast lights and analyzes how the existing lighting situation relates to perceptions of safety, perceived crime risk, and willingness to engage in public space at night. This article is relevant to social scientists in development economics, urban planning, and criminology in that it both demonstrates the importance of analyzing baseline data when conducting an RCT and provides new insight on access to public lighting in informal settlements.

As a jumping off point, this paper documents the limited research that exists on the efficacy of high-mast lighting as a public lighting option for informal settlements. Existing research has found that light must be both bright and uniform in order for people to report feeling safer and more confident in public space at night. This research informs public lighting standards in formal cities, yet there are no standards for informal settlements. Using nighttime light measurements collected in the informal settlement, I find that high-mast lights provide highly uneven light, both across the entire neighborhood and within individual paths.

Combining these measurements with household survey data, I find that there is only a relationship between light levels and respondents' perception of safety at night when light is bright — greater than 10 lux, on average. Meanwhile, the literature suggests that in formal cities a brightness level between 2–10 lux is sufficient for pedestrians to report feeling safe at night. I find no relationship between light levels and perceived risk of crime or willingness to engage in public space at night. When I replace light levels with distance from the high-mast light as the predictor of interest — a possible proxy when light measurements are not possible — I find results only differ slightly. Based on the literature, which emphasizes the importance of uniform lighting, these findings suggest that uneven lighting limits the positive benefits of public lighting even for residents living close to the lights on brightest paths because the rest of the neighborhood is not well lit. This research contributes to the understanding of effective public lighting technologies for informal settlements and is important for planners seeking to design development initiatives for these neighborhoods.

ARTICLE 4:
BRINGING LIGHT TO THE DARK — CAN SOLAR PUBLIC LIGHTING IMPROVE NIGHTTIME LIFE FOR THE URBAN POOR?

Finally, Article 4 is co-authored with Prof. I. Günther and evaluates the efficacy and impact of an alternative public lighting technology — wall-mounted solar public lights. This article speaks directly to the field of development economics, by estimating the causal impact of public lighting on the experience of life at night in informal settlements. This topic has been understudied, but has important implications for access to other types of shared infrastructure and quality of life in informal settlements. The article also contributes to various fields, including urban planning, criminology, and engineering, that study the link between public light and perceived safety, perceived risk of crime, nighttime activity in public space, and experience of crime. This RCT is the first, to our knowledge, to test the impact of public lighting in an informal settlement and only the second RCT studying the impact of public lighting on life at night.

For this study, we selected a wall-mounted solar outdoor floodlight as the treatment, which can be installed on the front façade of a house in an informal settlement. We apply a cluster-randomized controlled trial to test the efficacy and the impact of these lights as an alternative to standard streetlights. We find that areas that received solar public lighting were between six and eight times brighter than control clusters, partly because theft and vandalism of the lights were minimal. We also find that the treatment is linked to increased perception of safety. That said, a greater sense of safety did not translate to widespread changes in participation in most nighttime activities or experiences of crime. We did, however, find that residents in both treatment groups were more likely to use shared sanitation at night, which could indicate some degree of spillover, although we did not find widespread evidence of spillover effects on other nighttime activities or outcomes of interest. This finding is an important consideration for policymakers, as it indicates solar public lighting can facilitate access to shared sanitation at night. These results also add to the small body of experimental evidence of the impact of public lighting on life at night in an understudied context.

It is important to explain here that the original intent was that Articles 1, 3, and 4, would build on each other, with Articles 3 and 4 including pedestrian motion as an outcome variable in both analyses. Due to delays in the overall research project, primarily linked to the COVID-19 pandemic, as well as malfunction, theft, and vandalism of many of the sensors at different times, data could not be collected from enough sensors to effectively link the sensor data to the other data collected for the third and fourth article. Although the COVID-19 pandemic was not foreseen, the risk of malfunction, theft, and vandalism was a known possibility at the outset of the project given that this type of data collection had not been attempted, to my knowledge, in an informal settlement before. On the other hand, the COVID-19 pandemic was also the catalyst for the second article, which, of course, was not a possibility at the outset.

STATEMENT OF CONTRIBUTION

The concept for wall-mounted public lighting, which constituted the intervention in the RCT was developed as part of the doctoral work of S. Briers in the ISTP URI group. The idea to evaluate wall-mounted public lighting using a field experiment was my contribution to the initial idea for the collaboration. My research focused on quantitative evaluation of the project, while her research focused on the qualitative assessment of the project. My specific contributions to each of the four articles are as follows.

I contributed the idea to use sensors to measure pedestrian activity and led the work with Sensen to develop the concept for the sensors, as well as design and implement field tests. Sensen developed the pedestrian detection algorithm and built the sensors. S. Briers collaborated on the mapping of the informal settlement (along with local residents), provided her architectural opinion about installation materials, helped with an additional field test when I could not travel to South Africa, and participated in the installation of the sensors. In collaboration with Prof. I. Günther, I developed the sensor installation plan and data collection plan. Working with three local data collectors, Yamkela Rongwana, Jennifer Qongo, and Sibongile Mvumvu, as well as one research assistant, Erwin Lefoll, and Sensen, I oversaw all sensor data collection. All data cleaning and analysis for Articles 1 and 2 was done by me. I also wrote the initial draft for both articles. Major revisions of both drafts were jointly carried out by Prof. I. Günther and me. S. Briers provided minor comments on Article 1.

For Article 3, the single-authored paper, the research question was developed in discussion with Prof. I. Günther as part of the overall design of the RCT. The idea to collect light measurements in the informal settlement as part of data collection for the RCT was originally suggested by Prof. Kelsey Jack. I planned and oversaw the light measurement data collection and conducted all data cleaning. In collaboration with Prof. I Günther and with feedback from S. Briers, I developed the baseline survey instrument and the fieldwork plan. S. Briers and I collaborated on engaging with leadership in the informal settlement as well as the City of Cape Town and the local Ward Councillor to develop an infrastructure for the survey and to ensure that the survey also met the requirements for a Western Cape informal settlement enumeration. I led the data collection process in the field, conducted high-frequency checks, and cleaned the survey data. All analysis was conducted by me. Prof. I. Günther provided feedback on the analysis and the writing.

For Article 4, Prof. I. Günther and I co-developed the study design and randomization procedure as well as the endline survey. S. Briers and I collaborated on the development of what ultimately became a solar public lighting intervention and I supported the process of testing and ordering the lights for the intervention, which S. Briers led. I oversaw all endline light measurement and household survey data collection, which was carried out by field teams in the informal settlement, as well as all data cleaning, and analysis. Since we encountered problems with the light used in the intervention, I oversaw the repair of these lights in collaboration with Keyaam DuToit, a Cape Town-based lighting engineer and with engineering support from research assistant Daniel Rieben. I also managed the local maintenance during the intervention phase. K. DuToit and I collaborated to source the lights provided to all control households after the experimental phase of the project was complete. I wrote the initial draft of Article 4. Prof. I. Günther and I jointly carried out revisions.

ARTICLE 1: **PREDICTING PEDESTRIAN ACTIVITY IN INFORMAL SETTLEMENTS**

Status: Working Paper

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1. INTRODUCTION

Pedestrian mobility in cities is a common topic of study for urban planners, but the focus is almost always on the formal parts of cities (Jacobs, 1961).[2] Little is known about the pedestrian life of residents from informal settlements (Anciaes et al., 2017; Cutini et al., 2019; Hillier et al., 2000; Mehta, 2008; Salon & Gulyani, 2010) and even fewer studies have quantitatively analyzed pedestrian activity inside an informal settlement (Hidayati et al., 2020; Hillier et al., 2000; Mohamed, 2016).[3] Meanwhile, more than a billion people live in informal settlements worldwide (Dodman et al., 2018) and there is a growing realization in the urban studies community that informal settlements are the norm, rather than the exception, in many low- and middle-income countries (Simone & Pieterse, 2017). Moreover, *ad hoc* growth, reliance on shared water and sanitation infrastructure, and high vulnerability to crime and natural disasters together suggest that understanding how pedestrians navigate these neighborhoods can inform efforts to improve the experience of life in informal settlements as they grow in size and number globally.

We address this gap in knowledge about pedestrian activity in informal settlements by using novel pedestrian motion sensors installed throughout the path network in one informal settlement in Cape Town, South Africa. We measured pedestrian activity in the evenings and early mornings from October to November 2019. Using motion data and the structure of the network, we further analyze these patterns in the context of prevailing theories about pedestrian route choice to understand how well they explain empirical data from informal settlements.

Two general theories seek to explain how pedestrians choose routes based solely on network characteristics.[4] The first theory can be called route optimization, which posits that pedestrians choose routes by optimizing for a specific goal, such as shortest, fastest, or another optimal outcome (Willis et al., 2004). This theory is most commonly operationalized by calculating the shortest metric- or time-distance route. The shortest path is considered the dominant heuristic

[2] Jacobs (1961) is perhaps most famous for initiating this discourse.

[3] The United Nations defines an informal settlement as a place in which households experience one or more the following: lack of access to improved water source, lack of access to improved sanitation facilities, lack of sufficient living area, lack of housing durability and, lack of security of tenure (United Nations, 2020)

[4] Other theories exist, but they account for other variables besides the route network.

because it theoretically maximizes pedestrian utility (Zhu & Levinson 2015). As critics point out, however, the theory assumes pedestrians are cognizant of all alternatives and associated costs and can accurately optimize (Law and Traunmueller, 2018; Salazar Miranda et al., 2021).

Space syntax—the second theory— asserts that the configuration of the network is a core determinant of pedestrian activity and that various measures derived from the topology and geometry of the network can explain which routes people use most (Hillier, 2007; Hillier & Iida, 2005; van Nes & Yamu, 2021; Willis et al., 2004; Yamu et al., 2021). Indeed, Bill Hillier, considered one of the founders of space syntax, calls this phenomenon the law of natural movement and argues that the various parameters apply in nearly any urban space, from large cities to individual buildings (Hillier, 2007; Hillier et al., 1993).

There is an unresolved debate in the literature about which of these theories better explains pedestrian motion (Shatu et al., 2019). Yet, these theories are not necessarily mutually exclusive, as they are both variations of betweenness centrality (Javadi et al., 2017; Law & Traunmueller, 2018), but they differ in how much theoretical agency they ascribe to the average pedestrian in relation to her surroundings. Route optimization assumes pedestrians actively maximize utility *en route* to a destination, whereas space syntax assumes the configuration guides pedestrian intuition (Hillier et al., 1993).They also differ in how they operationalize the theory to derive measures of the network that predict route choice. While route optimization measures (e.g., shortest path) are based on metric distances, space syntax draws more on topological (direction change) and geometric (angular deviation) distances, although some measures also incorporate metric distance (van Nes & Yamu, 2021).

While various studies have analyzed how these theories apply to pedestrian activity in formal cities, predominantly in the northern hemisphere (Bongiorno et al., 2021; Hillier & Iida, 2005; Sharmin & Kamruzzaman, 2018; Shatu et al., 2019), very little work has questioned whether these theories apply in informal, unplanned neighborhoods (Anciaes et al., 2017; Hidayati et al., 2020; Mohamed, 2016). Yet, given the high density and frequently-shifting nature of informal street networks, it is unclear how much these two theories of pedestrian route choice explain actual pedestrian activity in informal neighborhoods.

Space syntax scholars Hillier & Iida (2005) ask "Why and how, then, should we expect street networks to shape movement in cities?" We both extend and focus this question by asking how an unplanned street network shapes movement in informal settlements, particularly in the early morning and evening hours, when most residents are typically leaving for or coming home from work.[5] We also ask how well existing theories, derived from movement patterns in high-income

[5] We observed that these are the time with the highest pedestrian motion in our dataset.

and formally planned cities, perform when it comes to predicting pedestrian activity in informal neighborhoods.

There are several reasons why movements in informal settlements might be different from formal settlements. First, the path network does not emerge from a gridded plan, but rather from many individual decisions (e.g., about where and how big to build houses) and community-level decisions (e.g., to block throughways to enhance safety). As a result, the path network is not static, but constantly evolving as residents' circumstances change. Second, activities which would be considered private in most formal areas, e.g., accessing basic services, like water and toilets, all frequently require residents of informal settlements to enter public space. Cutini et al. (2019) describes the paths in informal settlements as "spaces in between," because expectations about what is public and what is private space differ from expectations in formal urban areas. Third, informal settlements tend to be extremely dense, making it difficult to assess distances or other characteristics of the route by sight alone, especially if a pedestrian is unfamiliar with the area. Fourth, informal settlements are often not well integrated into the broader urban network, the way formal neighborhoods tend to be, influencing who enters these spaces (Karimi & Parham, 2012). Finally, informal settlements tend to have minimal or no public lighting, radically changing the experience of navigating a path network at certain times of day as compared to formal urban areas with adequate street lighting.

To address our two research questions, we apply shortest paths analysis (route optimization) and a space syntax analysis of pedestrian through-movement to the mapped path network of an informal settlement in Cape Town to predict movement patterns. We also directly measure movements between 6:00 pm and 8:00 am with novel sensor data. Correlating the path usage predicted by the two theory-based predictions with empirical data, we find that the shortest paths prediction is correlated with observed pedestrian motion in the evening hours, but not in the early morning. It performs equally well on weekdays and weekends. In contrast, we find no significant correlation between space syntax predictions of through-movement and measured pedestrian activity.

This paper makes two key contributions. The first is testing how well two theoretical frameworks about pedestrian route choice derived from formal cities in high-income countries compare to high-resolution pedestrian motion data gathered in a low-income informal settlement. The second contribution is the description and testing of pedestrian motion sensors for studying nighttime activity and route network usage within informal settlements. To our knowledge, this method has never been used before in an informal settlement and no studies have measured pedestrian activity in informal settlements at this level of granularity at night. This new approach was necessary because we found that GPS tracking on mobile phones would not work well in this context. These data, situated in the context of pedestrian route choice theories, can shape our understanding of what makes certain paths more "used" in informal settlements, where at least one-seventh of the world population lives (United Nations, 2020). The results can further guide both grassroots and government-level efforts to improve the accessibility of shared services and/or to upgrade these streets with, for example, streetlighting or better drainage.

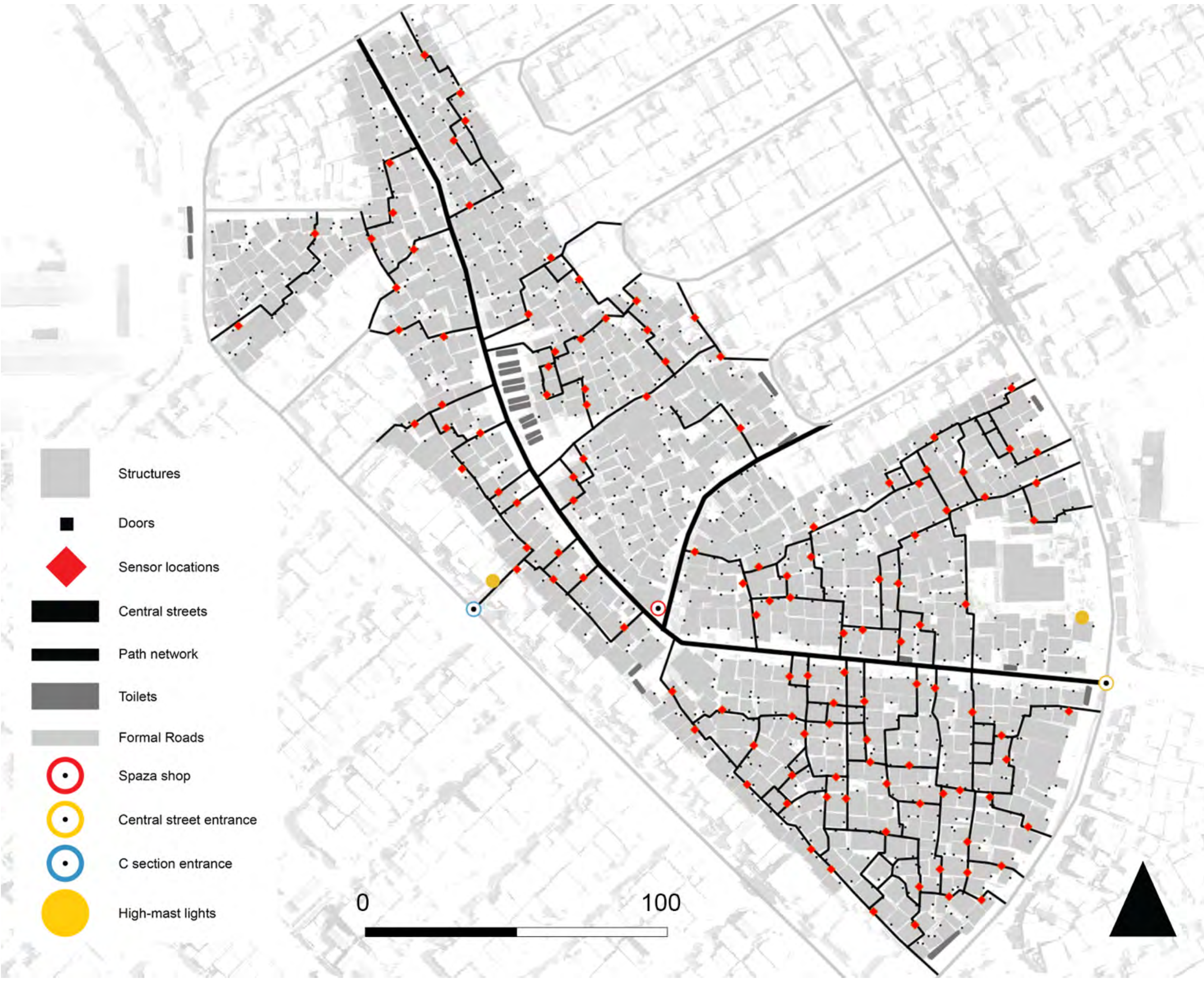
2. BACKGROUND OF CASE STUDY

In Cape Town, South Africa, there are more than 400 informal settlements, some of which predate the rise of democracy in the 1990s and others that are barely a year old. The informal settlement we study is approximately 30 years old and is about 38,200 square meters (Ndifuna et al., n.d.). It is located in Khayelitsha, a township created as a Black African neighborhood under apartheid, which lies on the outskirts of Cape Town. Known as a "pocket informal settlement," the neighborhood is surrounded by formal housing and streets. We began studying this site as part of a broader project focused on public lighting in informal settlements. One of the major reasons we selected this informal settlement is that the local community leadership committee was open to collaborating on our research.

Like many informal settlements worldwide (Kamalipour & Dovey, 2019), its path network was unmapped before we started this research project. To develop the path network, we used a satellite image of the informal settlement from early 2018 to facilitate orientation in physical space (City of Cape Town, 2018). Working with local leaders we traversed the area and drew all of the paths, dead-ends, and compounds, or shared semi-private cul-de-sacs that residents often close off with a gate. Improvements and corrections were made during a subsequent field visit, during which we also numbered each structure throughout the settlement, which facilitated improvements to the path network data.[6] Figure 1 shows the complete map of the informal settlement as of August 2019, just prior to installing the sensors.

[6] The house numbering was part of preparations to conduct a household survey and informal settlement enumeration, however, the process helped us to improve the map of structures, record the location of doors, and make corrections to the path map.

Figure 1. Path network map of the informal settlement



Data: Structures and path network mapped by authors in collaboration with two local leaders, Xolelwa Maha, and Thabisa Mfubesi; High-mast lights: City of Cape Town Public Lighting, Open Data Portal, 2019; Base Map: Aerial Photo, City of Cape Town Open Data Portal, Feb 2018.

The mapped path network can be classified into four main categories of paths, of which we only analyze the last one.

1. The *central streets* (bold black lines) bisect the neighborhood. Although they are sand covered, they are wider than all other paths and are passable with a vehicle. We refer to the long street that runs primarily east-west as the *horizontal central street* and the shorter street that runs north-south as the *vertical central street*. These streets are included in the shortest paths and space syntax through-movement calculations because they influence movement within the settlement, however, they were not monitored with sensors (and are not included in the comparative analysis) because the presence of cars as well

as large groups of people passing by would have biased the sensor measurements (see Section 3.1).

2. *Formal streets* (gray lines) are all of the paved streets surrounding the informal settlement that have both vehicular and pedestrian traffic. They link the informal settlement to the surrounding local economy (e.g., school, shops, transport, etc.). These streets are included in the shortest paths and space syntax through-movement calculations because they influence movement within the settlement, but they are not included in the comparative analysis as they were not monitored with sensors and are not part of the study area.

3. *Other components* (not pictured) include: compounds, which are collections of households that decide to block all access points to their houses except one shared and often gated entryway; and dead ends, usually created using a blockage constructed of corrugated iron and/or wood, that are used to prevent through-traffic. Compounds will not be included in our analysis as the theoretical models would not have any predictions about the movement we observe.

4. *Paths* (thin black lines) refer to the network of walkways that pedestrians use to get from one part of the settlement to another or to the formal areas surrounding the informal settlement. To determine sensor placement (red squares), the paths were divided into *path segments* based, as much as possible, on turning decision (see Section 3.1). Only path segments are included in the analysis.

3. DATA AND METHOD

In the following section, we describe the pedestrian motion sensors used for tracking pedestrian activities and the sensor data in more detail. We then explain how we develop the theory-based shortest paths and space syntax through-movement calculations. The research project was approved by the ETH Zurich Ethics Commission (EK 2019-N-19).

3.1 SENSOR DATA

There are a wide variety of technologies used to study pedestrian activity in high- and low-income settings, from basic methods such as manual or observational counting (in person), video surveillance, GPS tracking with mobile phones, to various types of sensors such as laser, infrared beams, infrared optic, low ultrasonic frequency and treadle mats.[7]

[7] Examples of the use of these technologies in the academic literature range from manual counting (e.g., Cabaret, 2012; Hidayati et al., 2020; Mehta, 2008; Michelat et al., 2010) to increasingly technical methods such as video surveillance (e.g., Fujisawa and Hasegawa, 2012; Hidayati et al., 2020; Michelat et al., 2010; Tsuchikawa et al., 1995; Willis et al., 2004), GPS tracking on mobile phones (e.g., Bongiorno et al., 2021; Salazar Miranda et al., 2021), and various types of sensors (e.g., laser, infrared (IR) beams (e.g., Uttley and Fotios, 2017), IR optic, low ultrasonic frequency, and treadle mats (e.g., Letshwiti and Lamprecht, 2004)).

These approaches all have pros and cons, but for our setting a few criteria helped narrow the options. Manual counting would have been unsafe because fieldworkers would have to sit outside during dark hours.[8] Video surveillance was rejected due to privacy concerns. Although mobile phones are an increasingly used source of mobility data worldwide (Calabrese et al., 2013), a GPS tracking pilot we conducted in March 2019 demonstrated it would not work in the setting of a poor informal settlement for several reasons. First, a household survey we conducted in March 2019 revealed that only 37% of respondents carry a mobile phone when it is dark outside, for fear of having it stolen. Therefore, we would get a biased measure of nighttime activity. Second, GPS is inaccurate within a few meters, which is problematic when paths are narrow and houses are small and is even less accurate in informal settlements where building materials reportedly interfere with the signal. Since some paths are only a few meters apart, it would be difficult to determine which paths were used. Third, although many residents had a smart phone and were willing to participate, more than half of the residents who responded to our call for volunteers could not enroll because they did not have enough storage space for the app. Finally, not every resident has a smart phone, which would have again biased data on mobility patterns.

When considering sensors, it was essential that the device be resistant to hot, dusty conditions as well as intense rain, be simple to install on a variety of materials, be amenable to frequent data collection, and be relatively low cost to enable full path network coverage of the informal settlement. We collaborated with Sensen, a company that develops dataloggers, to design and implement the pedestrian motion sensors (Appendix A Figure 1).[9] Sensen developed the algorithm and designed the device based on our research questions and description of the context, then finalized the algorithm and design after a pilot study in a nearby informal settlement in February 2019.

Using a proximity infrared (PIR) sensor, the device recognizes a pedestrian by detecting differentials in thermal radiation (body heat), triggering the device to record a count. Every five minutes the sensor saves a trigger count and resets. No other details about individuals are recorded. We only use data between 6:00 pm and 8:00 am because the sensitivity of the PIR sensor prevents it from accurately measuring motion during the day, when thermal radiation from local building materials (e.g., zinc or corrugated iron) can lead to false triggers. To verify data quality, we conducted manual pedestrian counts between 5:00 – 7:00 pm, when many people are still outside and it is still safe to work, then compared the human-observed counts to the sensor data collected during the same time period.

[8] Between April 2019 and March 2020, Khayelitsha contained the police precinct with seventh most contact crimes in the entire country with 3,524 cases. The Khayelitsha police precinct also handled the second most murders in the country during the same time frame. Contact crimes include: murder, attempted murder, assault (grave bodily harm), assault common, aggravated robbery, common robbery, and sexual offenses (SAPS, 2020).

[9] More information about Sensen is available here: www.sensen.co

To determine where to install the sensors, we divided the path network into segments that are defined, as much as possible, by turning decision, similar to Weisburd et al. (2012) and Blattman et al. (2019). A path segment begins either at an entrance point from a formal area or at an intersection where a pedestrian can turn from one segment onto another. Since segments emerge or disappear as people build or demolish houses, the path segments do not have uniform length or width. Because of a limited research budget, we did not have enough sensors to monitor every single mapped path segment. To determine the final path segment sample, we left out short path segments that seemed redundant. In other words, segments that were probably only used by the residents who live on them. In total, we defined 133 path segments and left out 11 for this reason.

To introduce the sensors to the residents, we held community meetings to describe the purpose and function of the sensors and address concerns. The predominant concern was that some people would think the device was a camera and that the sensors would be stolen. Aside from these worries, there was widespread support for the study. Since sensors were installed on the outside of houses, we first met with the household head of any house that was a potential installation site to explain installation procedure and the purpose of the sensor, before asking for signed consent. If a household head did not provide consent, we selected another house on the same path segment.

We installed 122 PIR motion sensors on paths to measure pedestrian frequency in September 2019. The dataset for each sensor includes a value (number of pass-bys) for every five-minute period in which the sensor is activated and functional from October 1, 2019 through November 30, 2019. Throughout the course of the study, some sensors were stolen/vandalized and some sensors started to malfunction (e.g., discharged battery). To adjust for attrition, we drop data from all sensors that did not function properly throughout the entire data collection. To allow for minor, random data loss caused by Bluetooth connection issues, we include all sensors that had data on a minimum of 54 days, as long as the missing days are not clumped at the end of the study period (indicating malfunction, theft, or vandalism).

In total, 78 sensors functioned for the entire study period and produced 787,121 five-minute observations for the hours between 6:00 pm and 8:00 am. The data can be interpreted as the number of individuals passing the sensor in each five-minute period. To collect the data, three trained residents used a Bluetooth-enabled mobile phone application developed by Sensen to connect to each sensor and download the data. Data could then be uploaded to the Sensen server over an internet connection. The data collectors collected data every other week and always worked during the daytime.

While sensors make it possible to measure high-frequency nighttime pedestrian activity in an informal settlement over an extended period, they also have limitations. First, they do not accurately measure daytime activity, which limits our ability to study differences between day and night as well as compare our findings with existing work that has mainly monitored daytime pedestrian activity in informal settlements. Second, there are problems with occlusion. That is, the sensor will not count each individual if two or more people are inside the sensing field at the same time. Since the paths we measure are generally narrow (on average, less than two meters wide), this should not occur too often, but we are still likely to undercount when multiple people pass the sensor at the same time. Since this problem affects all sensors equally, we may underestimate the true level of activity overall.

Even though existing theories on pedestrian movement do not differentiate between different times of the day or week, we compare the theoretical predictions of pedestrian mobility to the five-minute mean calculated for all hours in which we have data (6:00 pm – 8:00 am), for the evening (6:00 – 9:00 pm), the early morning (5:00 – 8:00 am), weekday (Mon – Fri), and weekends (Sat/Sun) separately, in order to check whether time plays a role pedestrian activities and the predictive power of existing theories.

3.2 SHORTEST PATH ANALYSIS

Shortest-path analysis is the simplest application of route optimization theory and is most frequently operationalized for pedestrian route choice using Dijkstra's shortest path algorithm (Golledge, 1995; Law & Traunmueller, 2018), which calculates the shortest distance between any two nodes (origin-destination pairs) in a network using the length of street as edge weights (Dijkstra 1959). In the context of informal settlements, this approach has been used as an input to evaluations of infrastructure accessibility (e.g., Holderness et al., 2013; Schmitt et al., 2017), however, it has not appeared to played a role in studies of pedestrian activity in these neighborhoods, perhaps because there is hardly any research on the topic.

To determine the most frequently used paths under the route optimization framework, we use the Shortest Path algorithm in QGIS (version 3.10). First, we choose origin-destination pairs that are relevant to most residents in the community. All the doors that have been mapped on each structure are considered origins (N = 869) and three separate sites within the informal settlement path network are considered destinations: 1) the largest Spaza shop (convenience store) in the center of the settlement, 2) an entrance/exit near the western high-mast light that residents frequently use to access the nearby shopping center and transportation, 3) the main eastern entrance/exit, which connects to a formal road with shops, a taxi drop-off points, and the local high school (see Figure 1). Although shared toilets are used by most residents, we do not use toilets sites as a destination because there is one large grouping of toilets not far from the Spaza shop and many more distributed throughout the settlement, but we do not know which houses use which site.[10] As a result, we selected sites that we know, based on a fieldwork, that a majority

[10] In this informal settlement it is common that several households share one toilet stall and keep others out by installing a lock on the door.

of residents use frequently. In addition, since the Spaza shop is not far from the large collection of toilet blocks, it is likely we capture many of the same shortest-path routes.

The algorithm calculates the shortest path between each origin and destination specified in the network (see Appendix A Figure 2 for a map of the shortest path calculation for each scenario). We then compute the number of times each segment is part of the shortest path for each origin-destination pair (i.e., betweenness centrality) to determine the most frequently used path segments for each scenario (Law & Traunmueller, 2018). The result is a count for each path segment under each of the three shortest-path scenarios (i.e., the largest Spaza shop, Western entrance/exit called 'C Section entrance', Eastern entrance/exit called 'Central streets entrance'). The prediction of overall path usage frequency is calculated by taking the average of the three shortest-path scenario counts.

3.3 SPACE SYNTAX

Space syntax techniques for analyzing human activity proceed from the assumption that "what happens in any individual space – a room, corridor, street or public space – is fundamentally influenced by the relationships between that space and the network of spaces to which it is connected" (UCL Space Syntax Group, 2021).[11] The two main measures used to describe the relationship between the spatial network and the pedestrian activity that happens along it are *integration* and *choice*. Integration can be thought of as a measure of *to movement*, or an indicator of where pedestrians go (e.g., shops), while choice can be thought of as *through movement*, or an indicator of how pedestrian activity is distributed. In other words, integration predicts the likelihood that a street segment is part of a trip for all origins and destinations in the network. Choice is a measure of the frequency with which a segment is on the shortest path between all path segments within a prespecified distance, referred to as the *radius* (r). In this case, the 'shortest path' is not the metric shortest path, but rather the path with least angular deviation (van Nes & Yamu, 2021). Each measure can be calculated at different radii, with higher values oriented more towards global movement flows and small radii to local ones (van Nes & Yamu, 2021).[12] Thus, like the results of the shortest path analysis, choice is also a measure of betweenness centrality (Law & Traunmueller, 2018). In this paper, we focus on choice, rather than integration, because it is most comparable to the sensor data and our measure of path usage based on the shortest path analysis.

To calculate choice, we use depthmapX (0.35b), developed by the Space Syntax Group at the University College London (UCL), to run an angular segment analysis on the informal

[11] This is the explanation provided on the official space syntax website (UCL Space Syntax Group).

[12] It is recommended to calculate metrics like choice at different radii, depending on what level of the hierarchy of urban streets you are interested in understanding. Smaller radii, relative to the size of your study site, is expected to explain local level movement, while larger radii might explain more about movement on major arteries in the area. When radius is equal to n (r = n), the entire study site is taken into account and this is considered the global measure (van Nes & Yamu, 2021).

settlement route network, plus the immediately surrounding formal roads. Angular segment analysis accounts for curved streets and other irregularities by assuming that pedestrians are influenced both by the connectivity of the network and by angles in the network and that they choose routes that minimize direction changes (angular deviation) (Dalton, 2003). These assumptions are particularly relevant in an informal settlement, where minimizing angular deviation can be complex. For a detailed explanation of angular segment analysis see van Nes & Yamu (2021).

While studies often report choice at several different radii up to and including *n* (the global measure which encompasses the entire study site), we focus specifically on choice measurements at radii that are informed by our knowledge of the area. The intent is to avoid spurious correlations that could come by testing correlations at many radii and finding a correlation by chance, which has been a critique of the space syntax literature (Ericson et al., 2021). Since half the length of the horizontal central street is between 150 and 200 meters, we focus on radii of 150 meters and *n* (the global measure) based on the hypothesis that 150 meters best represents local movement inside the settlement and a radius of *n* should capture movement into the formal areas.

Both theories discussed here take a relatively narrow view on the fundamental drivers of pedestrian route choice. Although there is a much broader walkability literature that theorizes and tests a board range of variables that can also influence the route select process — e.g., personal characteristics such as age, gender, and mobility; environmental characteristics, such as slope and weather; sense of place characteristics, such as perception of safety, accessibility, desirability, and more (Lo, 2009; Salazar Miranda et al., 2021a) — we focus solely on route optimization using shortest paths analysis and space syntax using the measure of choice because our data contain no information about the people who pass the sensors.

4. RESULTS

Since the theory-driven calculations of path usage patterns are not directly translatable to numbers of pedestrians passing by (as our empirical measures are), for all maps we split the data into tertiles — low (blue paths), medium (yellow paths), and high (red paths) — such that an equal number of path segments are in each, making visual comparison between theory-driven calculations and empirical measurements easier. Any path segments without a sensor (and hence no empirical data) are black if they are within the informal settlement (including the central streets) and gray if they are a formal road. Finally, to improve readability of descriptive results, we further divide the settlement into four quadrants (A, B, C, D); see Figure 2.

4.1 OBSERVED PATH USAGE FROM SENSOR DATA

Over the study period, the average five-minute motion is 1.99 triggers — about 23.8 triggers per hour (Table 1). The averages in the evening (6:00-9:00 pm) with 55.4 triggers and in the morning (5:00-8:00 am) with 28.2 triggers per hour are higher. Also, movement on weekends is higher than movements on weekdays.

Table 1. Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Sensor					
Avg. 5-min Motion	78	1.996	1.154	0.093	7.361
Avg. Evening 5-min Motion (6-9 pm)	78	4.618	2.058	0.156	9.997
Avg. Morning 5-min Motion (5-8 am)	78	2.358	1.795	0.162	8.099
Avg. Weekday 5-min Motion (Mon-Fri)	78	1.917	1.167	0.090	7.831
Avg. Weekend 5-min Motion (Sat/Sun)	78	2.199	1.188	0.098	6.112

The summary statistics for average path usage measured by sensors is about 23.8 triggers/hour overall, 55.4 triggers/hour in the evening, 28.2 triggers/hour in the morning, 23 triggers/hour on weekdays, and 26.4 triggers/hour on the weekends, on average.

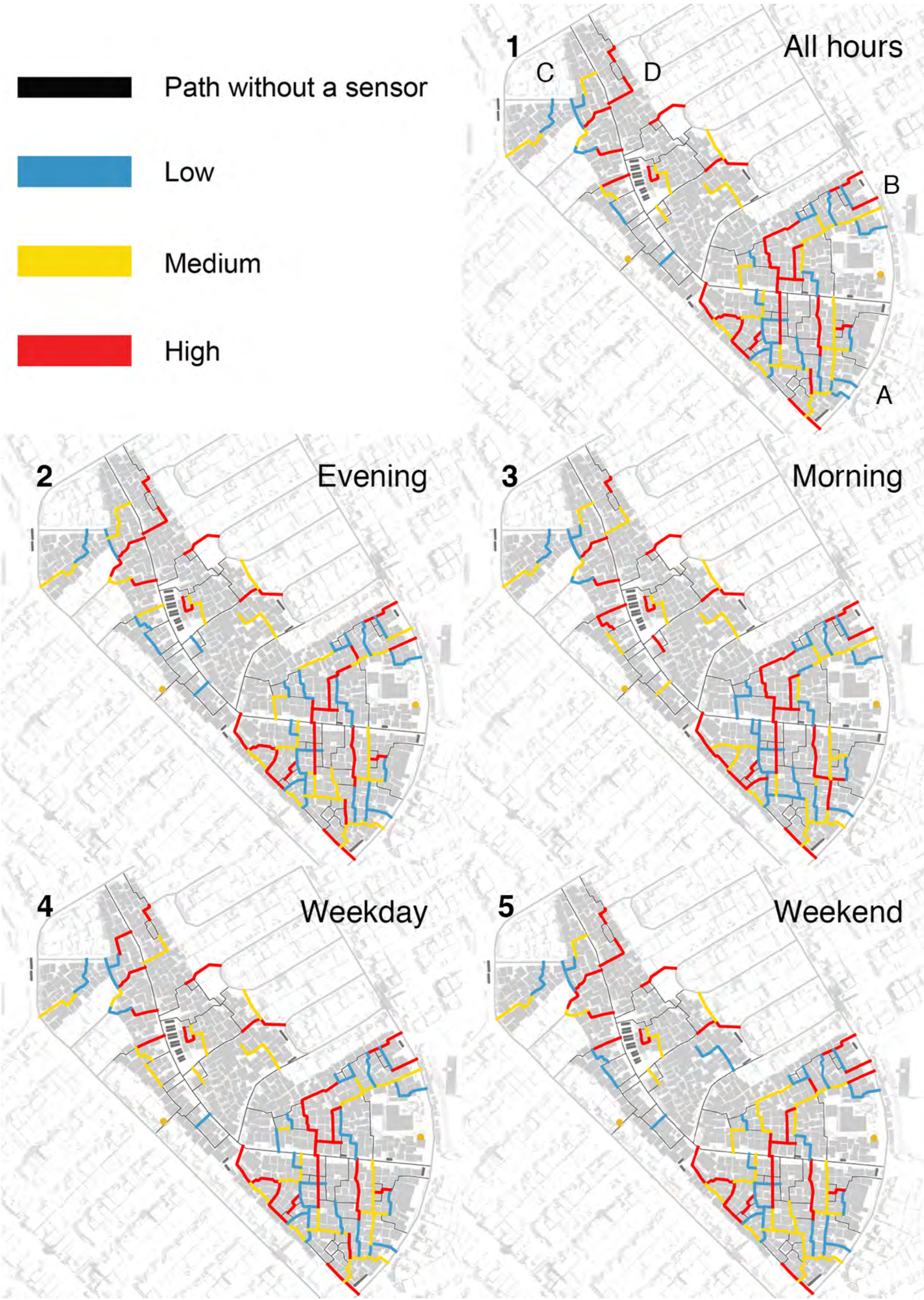
Figure 2 maps the path-level five-minute averages for each time interval: all hours (6:00 pm – 8:00 am), evening (6:00 – 9:00 pm), morning (5:00 – 8:00 am), weekdays (Mon. – Fri.), and weekends (Sat/Sun). The highest activity paths vary across the different time intervals. Morning and evening high-use paths are noticeably different, not just because there are fewer high-use paths in the morning, but also because several paths that are high use in the morning are not in the evening. This could be explained by different types of activities taking place in the early morning compared to the evening. For example, social activities may cause more triggers at night and be more common in some paths than others. Weekday and weekend activity are not hugely different, though there are more high-use paths overall on the weekend, reflecting the fact that many more people are home. Entrances and exits to the informal settlement seem to be in particularly high use at all the times we study reflecting interaction between the informal settlement and the area surrounding it.

To support the visual analysis, we calculate the correlation coefficient between the different time periods (using the value, not the categories). Scatterplots are shown in Appendix A Figure 7. Comparing evening and morning average motion to each other, it is clear morning and evening activity is different — the correlation coefficient is 0.42 ($p < 0.01$, $R^2 = 0.17$). For weekends and weekdays, the maps in Figure 2 indicate that the distribution of pedestrian activity across paths is similar, which is supported by a 0.92 correlation coefficient ($p < 0.01$, $R^2 = 0.84$), indicating strong correlation of paths used (even if at a higher level on weekends).

It is important to note that since South Africa is in the Southern Hemisphere, days are getting longer and warmer throughout the study. On October 1, 2019, sunset and sunrise are at 6:48 pm and 6:23 am and at 7:41 pm and 5:28 am on November 30, 2019 — two hours of additional daylight. Thus, our evening and morning averages, capture quite a bit of daytime activity.[13]

[13] South Africa does not observe Daylight Savings Time.

Figure 2. Five-minute average by path segment



The map shows the average number of pedestrians per five-minute period per path for each time interval: all hours (6 pm – 8 am), evening (6 – 9 pm), morning (5 – 8 am), weekdays (Mon – Fri), and weekends (Sat/Sun).

4.2 PREDICTIONS OF PATH USAGE FROM SHORTEST-ROUTE AND SPACE SYNTAX ANALYSIS

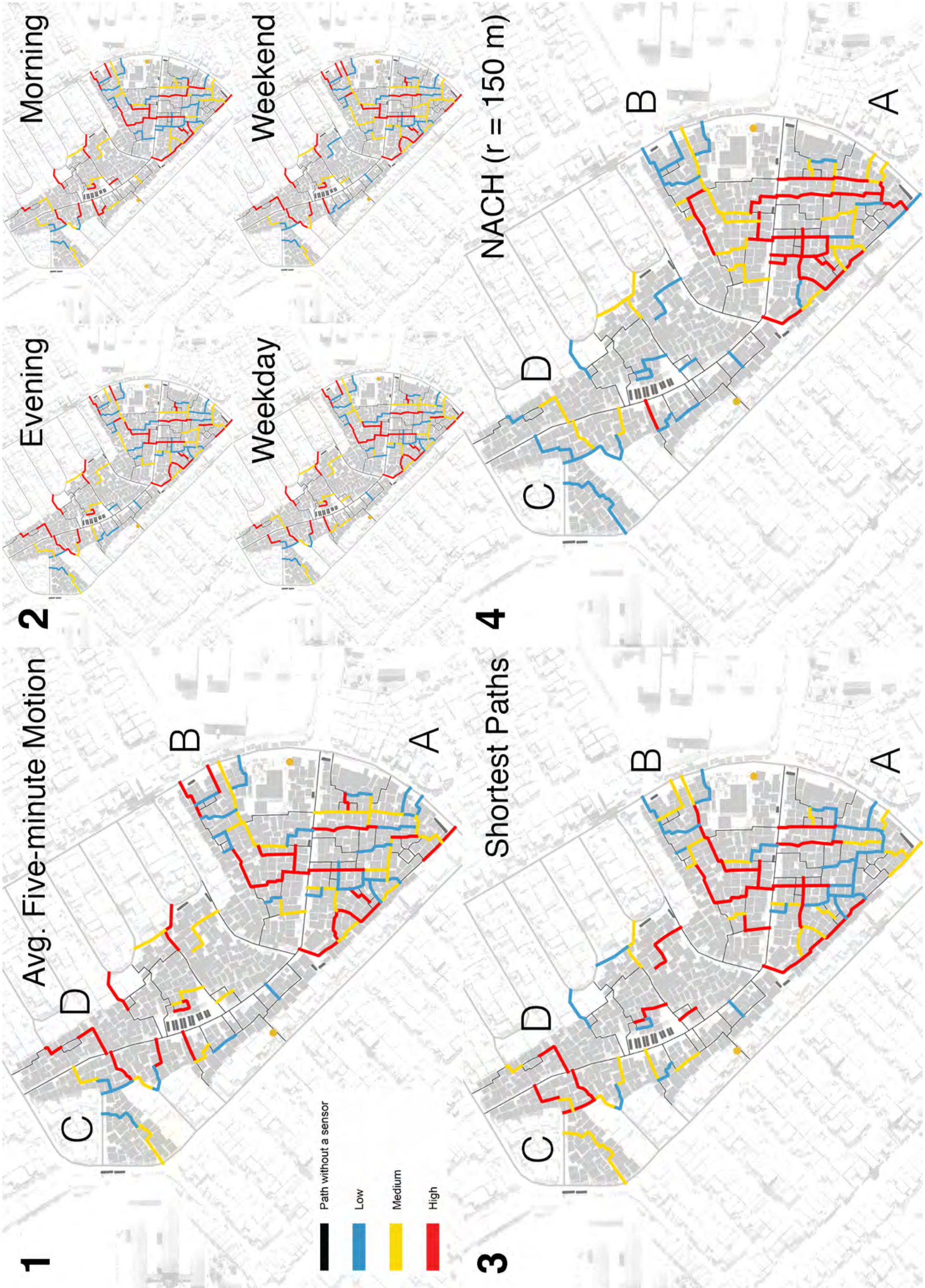
Figure 3 maps the two theory-driven measures (based on Appendix A Figures 3-5), but does not include unmonitored paths for which we do not have sensor data. We only show the results from the measures of normalized choice where radius = 150 meters in Figure 3 (see Appendix A Figure 6 for *n* radii), because this radius captures the region that is most relevant to activity inside the informal settlement. We report the summary statistics for the shortest paths and choice calculations in Appendix A Table 1, as well as the maps showing the distribution of path usage by each theory-driven calculation in Appendix A Figures 3-5.

Comparing the shortest paths calculation (Panel 3, Figure 3) to the sensor measurements (Panel 1, Figure 3), we see that the predictions are reasonably close to the sensor predictions in sections A and B, where the network is complicated, but it tends to slightly underpredict activity in C and D sections, where the network is relatively sparse. The normalized choice calculation (space syntax), on the other hand, heavily over-predicts activity in A and B section (especially on weekdays and in the morning), heavily under-predicts the sensor measurements in D section, but seems to predict activity in C section somewhat better.

Where both theory-driven calculations (shortest paths and choice) fall short is at the entrances. In the sensor measurements, all entrances into the informal settlement from the formal areas are either medium (yellow) or high (red) usage, but neither theory-driven calculation predicts these path segments to be in high use.[14]

[14] In Appendix A Figure 6, the map of normalized choice values (radius = *n*) does predict high usage values for all entrances/exits, but these predictions overestimate the usage of several entrances, likely contributing to the fact that normalized choice (radius = *n*) is also not correlated with the sensor data.

Figure 3. Mapped comparison between the two theory-driven calculations



4.3 CORRELATION BETWEEN PREDICTIONS AND OBSERVED PATH USAGE

Van Nes & Yamu (2021) argue that the space syntax literature demonstrates that angular segment analysis appears to be the best predictor of pedestrian movement, while "[m]etric distance is a distant third." We test this hypothesis by comparing one element of angular segment analysis, normalized choice, and metric distance (via the shortest path analysis) in the informal settlement with observational sensor data by calculating a Pearson pairwise correlation coefficient between predicted and observed pedestrian activity. The correlation coefficient (R) indicates how related each of the measures are to each other and makes it possible to assess whether the predictions of one theory might show a higher correlation with the sensor measurements.[15] In addition, we also report the R^2 since this value is sometimes reported in the space syntax literature instead of the correlation coefficient and because R^2 is commonly used across social science disciplines (Table 2).

Table 2 reports the results of the analysis (see Appendix A Figures 8-12 for scatterplots). In row 1 we show the correlation of the five-minute mean for each path for each time period with the shortest paths measure — the average count across all three shortest path scenarios. Rows 2 and 3 report the correlation with normalized choice at a radius of 150 meters and *n*. The correlation results confirm the impressions from the maps. There is generally a low correlation between usage patterns predicted by theory and usage patterns as observed with sensor data. We find the highest correlation between the shortest path calculation and evening average pedestrian motion ($R = 0.39$, $p < 0.01$). The correlations between the shortest path calculation and average motion (6 pm – 8 am), weekday motion (Mon-Fri), and weekend (Sat/Sun) motion are all smaller. We find no statistically significant correlation between either of the normalized choice calculations from space syntax and the measures of average five-minute motion for any time period.

[15] Since interpretation of the strength of the correlation coefficient varies across fields, we follow van Nes & Yamu (2021) in interpreting $R < 0.3$ to be no/very weak correlation, $0.3 < R < 0.5$ to be a weak correlation, $0.5 < R < 0.7$ to be moderate, and $R > 0.7$ to be strong.

Table 2. Correlation between the average five-minute motion in different time intervals and the theory-driven calculations

	Avg. 5-min Motion				
	All (1)	**Evening** (2)	**Morning** (3)	**Weekday** (4)	**Weekend** (5)
Shortest Paths					
Avg. Count	0.25/0.06 (0.03)	0.39/0.15 (0.00)	0.15/0.02 (0.20)	0.23/0.05 (0.04)	0.29/0.08 (0.01)
Space Syntax					
Norm. Avg. Choice (radius = 150 m)	0.01/0.00 (0.92)	0.16/0.03 (0.15)	-0.05/0.00 0.63	-0.01/0.00 (0.93)	0.07/0.00 (0.57)
Norm. Avg. Choice (radius = *n*)	-0.08/0.01 (0.50)	0.05/0.00 (0.69)	-0.11/0.01 (0.34)	-0.08/0.01 (0.48)	-0.06/0.00 (0.59)

Notes: The table reports the Pearson's pairwise correlation coefficient (*R*) on the left of the slash and the R^2 on the right. The p-value is in parentheses. We consider a correlation significant if the p-value is 0.05 or less.

5. DISCUSSION

Although the small number of papers on pedestrian activity in informal settlements have used space syntax (and not shortest distance metrics) to predict pedestrian flows (Hidayati et al., 2020; Mohamed, 2016), we do not find the space syntax measure of choice to be a better predictor. When we compare measures of choice (150-meter and *n* radii) and a shortest (metric) paths prediction of most frequently used path segments to empirical data gathered using novel proximity infrared sensors, we find that the shortest paths prediction explains more of the variation we measure with sensors. Moreover, the visual comparison of the two theory-driven predictions and sensor averages reveals that the shortest paths calculation performs better in the areas of the informal settlement that have more complicated route configurations. Furthermore, the theory-driven measures very poorly predict the level of activity recorded at the entrances/exits of the informal settlement.

To our knowledge, no study has compared shortest paths (route optimization) to pedestrian data from informal settlements. In formal areas, pedestrian routes have been found to deviate from shortest path routes, as the routes pedestrians walk get longer (Bongiorno et al., 2021).

In the space syntax literature, our study is not the first to find weak correlations between predictions and empirical measures in informal settlements. Hidayati et. al (2020) do not report correlation coefficients, but the qualitative comparisons between choice analysis in a Jakarta informal settlement and the video footage reveal that some segments have far fewer pedestrians than predicted. They attributed this inconsistency to non-network characteristics, such as building size and land use. Mohamed (2016) studied two different informal settlements in Cairo and conducted manual pedestrian counting during several time periods (including from 6:00 – 8:00 pm) in a single day. In one settlement, they find a reasonably strong, significant correlation between measures of choice at larger radii (1200 m, 2000 m, and *n*; R^2 = 0.42, 0.56, 0.44, respectively) and pedestrian activity, but the coefficients were smaller and not statistically significant at local radii (800 m and 400 m). In another settlement, they find no correlation between choice (any radii) and pedestrian motion. In formal cities, the correlation coefficients between choice measures and manually measured pedestrian activity tend to vary, which has been a source of criticism (Ericson et al., 2021). A meta-analysis of 14 studies using various space syntax measures to study pedestrian movement confirmed, based on the six studies that analyzed choice, that it is predictive of pedestrian movement in cities and neighborhoods of high-income countries (Sharmin & Kamruzzaman, 2018). When they looked at the correlation coefficient between choice and pedestrian movement individually, however, they found it to vary between R = -0.141 in a study Sodermalm, Sweden (radius = 500 m) to R = 0.885 in another study in Bakirköy, Istanbul on the weekend (the weekday correlation coefficient was only slightly smaller) (Sharmin & Kamruzzaman, 2018).

The notion that informal settlements, or *unplanned settlements* as scholars in the space syntax literature also refer to them, have unique characteristics (i.e., irregularity) that might mediate the relationship between the network and pedestrian activity has already been acknowledged in the space syntax literature (Karimi & Parham, 2010, 2012). Yet, our study, in combination with the small number of other studies points to an important insight. While choice may be as predictive as expected when it is compared to observed data from cities that *include* informal settlements, it may lose most of its predictive power when studying a local informal network by itself and might even perform worse than the simpler shortest path analysis. In the particular informal settlement we studied, five possible explanations come to mind.

First, the space syntax measure of choice does not account for path width, however, some path segments in this informal settlement are so narrow that a pedestrian must turn sideways to use it. Therefore, even though the segment may appear geometrically, topologically, and metrically ideal, few pedestrians may use that segment in actuality because it is so uncomfortable. Lack of consideration for path width would also explain some shortcomings of the shortest paths analysis. The physical ability to fit through a path segment is simply not an issue of consideration in formal cities, but it is an important one in this context.

Second, Hillier et al. (1993) write that "configuration may affect movement, but configurational parameters cannot be affected by it." In this informal settlement, that assumption may not be valid. On each visit to the informal settlement, invariably a new compound, or cul-de-sac, had been created by a group of residents blockading a path because the amount of through-traffic made them feel unsafe, demonstrating that in this setting movement can affect configuration.

Third, few residents had ever seen a map of the informal settlement route network. Therefore, residents seem to rely on a mental map of landmarks to go from point A to point B. Our field team described their navigational approach as one oriented toward getting to a central street or main road as quickly as possible, rather than walking through smaller path ways. Such a strategy makes sense if you want to avoid very narrow paths, are concerned about safety in a smaller path where fewer people are, and/or if the smaller paths are darker at night. Perhaps the desire to quickly reach main arteries or formal areas counteracts the lack of information about distances and makes shortest route distances a better prediction of pedestrian mobility. Moreover, this behavior of quickly reaching the main roads could explain why exit paths (see Figure 3) are much more used than would be predicted by any of the theories. Underprediction of entrances/exits might however also be linked to the size of our study area, however, using normalized choice (rather than the raw choice calculation) is intended to control that problem.

A fourth explanation why shortest route might be more predictive could be the ease with which pedestrians can figure out how to navigate space (Hillier et al., 1993). One important insight we learned from fieldwork is that residents typically only know the quadrant where they live and rarely, if ever, walk on path segments in other quadrants of the informal settlement. Hence, the critique that residents lack much of the information necessary to select the optimal path and may unintentionally forego shorter routes might be misplaced as most people who navigate the space know it well from experience. Furthermore, as this is a residential area, it may be that the majority of motion we measure is generated by those that have sufficient experience to recognize the shortest path, compared to areas that have a large number of pedestrians who have little familiarity with network.

A fifth reason why shortest paths analysis may perform better than choice lies in the assumptions behind the calculations. Angular segment analysis accounts for direction change, whereas the shortest paths analysis simply measures the shortest metric distance between origin-destination pairs. In this informal settlement network, however, there are sometimes superfluous bends in the paths wherein a pedestrian might not perceive a direction change, but there is angular deviation in the path segment map that is captured in the calculation (see Figure 1). Therefore, it is possible that some segments are unduly penalized as a function of the formula. This idea could be tested by future research using sensitivity analysis. As with Karimi's (2002) study of old, "organic cities" in Iran, it is possible that certain adjustments must be made to the space syntax methodology in order for it to more effectively predict pedestrian flows in informal settlements.

Last, by comparing the theory-driven measures to the average motion in the evening and the morning, we also highlight what might be an important variable that these theories do not address: time. As we demonstrated, correlation coefficients were highest for the evening average and lowest for the morning average. Yet, the difference in the correlation analysis indicates that the distribution of activity throughout the informal settlement is not very similar. One explanation could be that activity in informal settlements in the evening is representative of a broader range of activities including evening commute, shopping, using the shared sanitation infrastructure, and socializing happening in public space (Cutini et al., 2019, 2020; Kamalipour, 2020), while activity in the morning may be more limited in ways that create differential patterns, as people are primarily focused on the activities required to start their day (e.g., using the toilet, commuting, etc.).

It is important to caveat our findings by first pointing out that we do not have sensor data for all path segments. That said it is important to point that the theory-driven calculations were based on the entire network no matter whether we monitored the path segment with a sensor or not. Still, out of 122 path segments that had a sensor, we do not have a sensor measurement for 44 segments, which limits our knowledge of movement patterns. Although we addressed sensor attrition by only including path-segment level observations from the shortest paths and the choice calculations for which we also have sensor data, we cannot rule out that sensor data for the missing 44 paths would not change correlation coefficients.

Furthermore, the sensors do not accurately measure pedestrian motion during peak daylight hours, meaning that the hours we measure do not correspond with all of the time windows space syntax methodology recommends for manual measurement (van Nes & Yamu, 2021). However, since this informal settlement is primarily a residential area, the evenings and mornings are when the majority of people are in the neighborhood, rather than out at work. In addition, we only use three scenarios to construct the shortest paths calculation, thus it is possible that considering many more scenarios would lead to higher correlation coefficients. Finally, other studies employing space syntax frequently include a very large study area, whereas we conducted our angular segment analysis on a relatively small area, defined by the boundary of the informal settlement and the immediately surrounding formal roads. We selected this area since we focus only on pedestrian, rather than both pedestrian and vehicular activity, however, it is possible that this has an impact on the analysis, since we do not know for sure how much pedestrian activity outside the settlement influences pedestrian activity inside of it.

6. CONCLUSION

Using pedestrian motion sensors to measure pedestrian activity in evenings and early mornings, we were able to analyze the mobility pattern in an informal settlement and test how two common, and in formal cities validated, theory-driven approaches to predicting pedestrian route choice perform in comparison to the data. The highly-detailed sensor data allow us to analyze, over a longer period of time and at a high degree of granularity, the extent to which previous findings about these foundational theories hold. Our findings fit with the relatively small number of studies that find space syntax measures of choice are weakly or inconsistently correlated with pedestrian activity in informal settlements. To our knowledge, no studies use route optimization approaches like shortest paths analysis in informal settlements.

When we analyzed the sensor data by itself, we find evening and morning average motion are rather different, whereas weekend and weekday average motion are strongly correlated, though weekend activity seems to be more intensive. Comparing the sensor data to the theory-based predictions, we find that the shortest paths calculation is correlated with the sensor averages to some extent, while the space syntax measure of choice was not significantly correlated under any scenario.

These findings open up important considerations for future work to further develop what drives pedestrian activity in informal settlements and what makes some paths more used than others. Empirically measured pedestrian activity may deviate from existing theories that only account for characteristics of the route network for several reasons, including: extreme density and narrow path width, the constantly changing configuration of the network, residents' reliance on mental maps given that it is common for informal settlements to be unmapped, the possibility that measured activity may be dominated by residential activity rather than through-traffic from other areas, and finally due to the differences in the types of activities that take place in the morning compared to at night in an informal settlement. As a result, there may be a stronger limit to the explanatory power of network-focused theories, compared to formal areas, necessitating theories that more directly consider the nature of pedestrian behavior in informal neighborhoods.

Informal settlements make up a large and growing share of the urban environment throughout Africa, Asia, and Latin America. There is already an increasing push to facilitate incremental improvements that work with the existing informal settlement rather than to demolish and re-build with more traditional city planning techniques. Therefore, understanding the dynamics of pedestrian activity can provide key insights for local leadership as well as city planners aiming to improve accessibility to public service provision.

For example, fires are a common danger in informal settlements that force frequent re-building. With more information about pedestrian activity, community leaders and affected residents may be better equipped to make decisions about rebuilding that could improve access to escape routes or make it easier for firefighters to access the area. Even on a smaller scale, when one household wants to build a new structure or expand an existing one, communities can work together more effectively to make decisions that improve flows through the settlement. For city officials seeking to influence informal settlement development, a better understanding of pedestrian patterns could enable more informed decisions about the upgrading projects that do take place or influence the siting of shared services or public lighting.

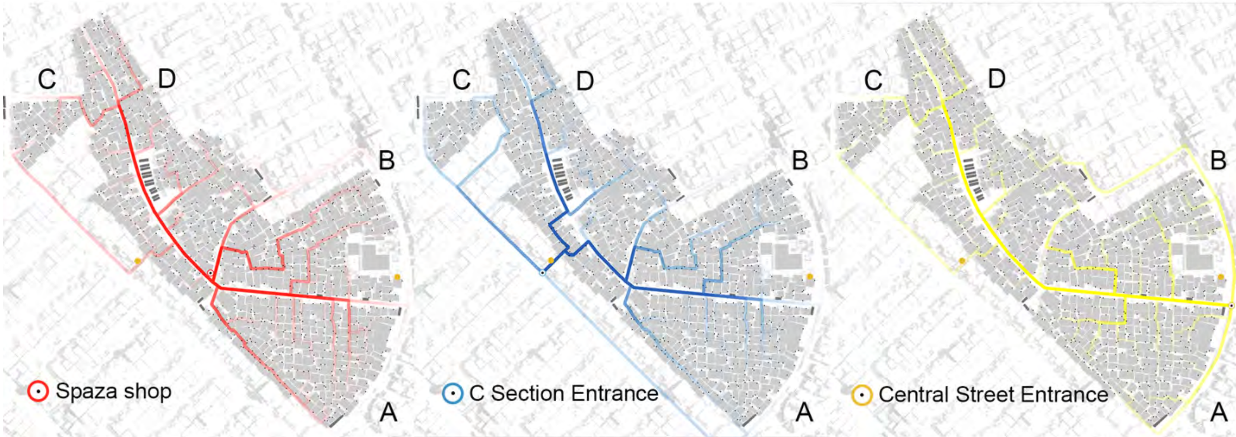
Finally, our study also shows that sensors are a minimally invasive, passive method for collecting data about pedestrian activity, especially at night when other measures might not work. Despite the challenges we encountered in deploying this technology in an informal settlement for the first time, we were able to gather highly detailed nighttime data about pedestrian activity to better understand how residents make use of the informal network and how well prevailing theories explain our observations. Future research could look at a variety of ways to improve pedestrian motion sensors in order to more effectively gather information that could enable improved service delivery, disaster response, and quality of life in informal settlements worldwide.

7. APPENDIX A

Figure 1. Pedestrian motion sensor

The pedestrian motion sensor (circled in yellow), co-developed with Sensen, is installed on a wooden fence in order to monitor a path in the informal settlement.

Figure 2. Shortest paths scenarios

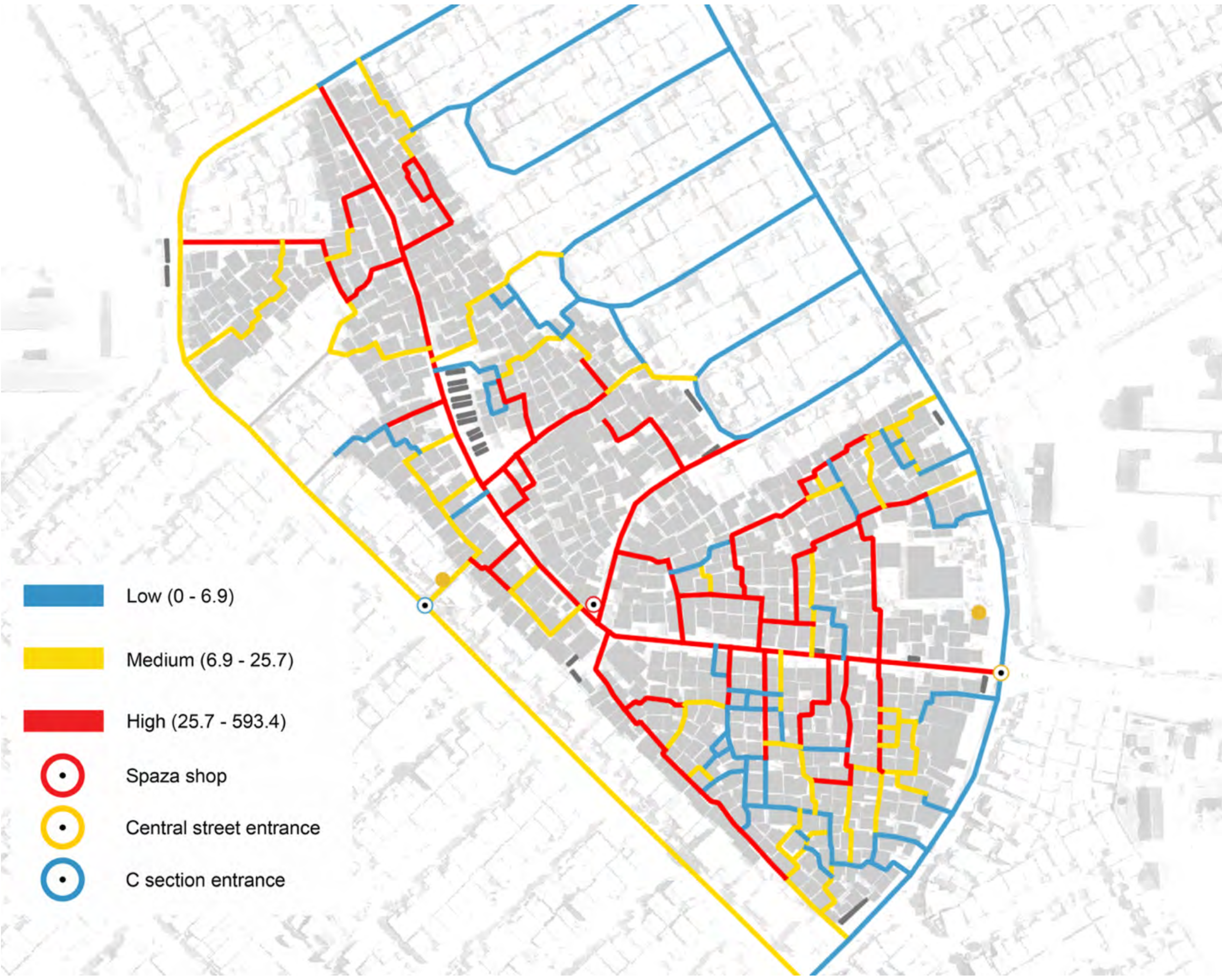


Most frequently used paths based on a shortest-path analysis for three scenarios (from left to right): 1) The central Spaza shop, 2) C Section (western) Entrance, 3) Central street (eastern) entrance.

Table 1. Summary statistics for shortest paths and choice measures

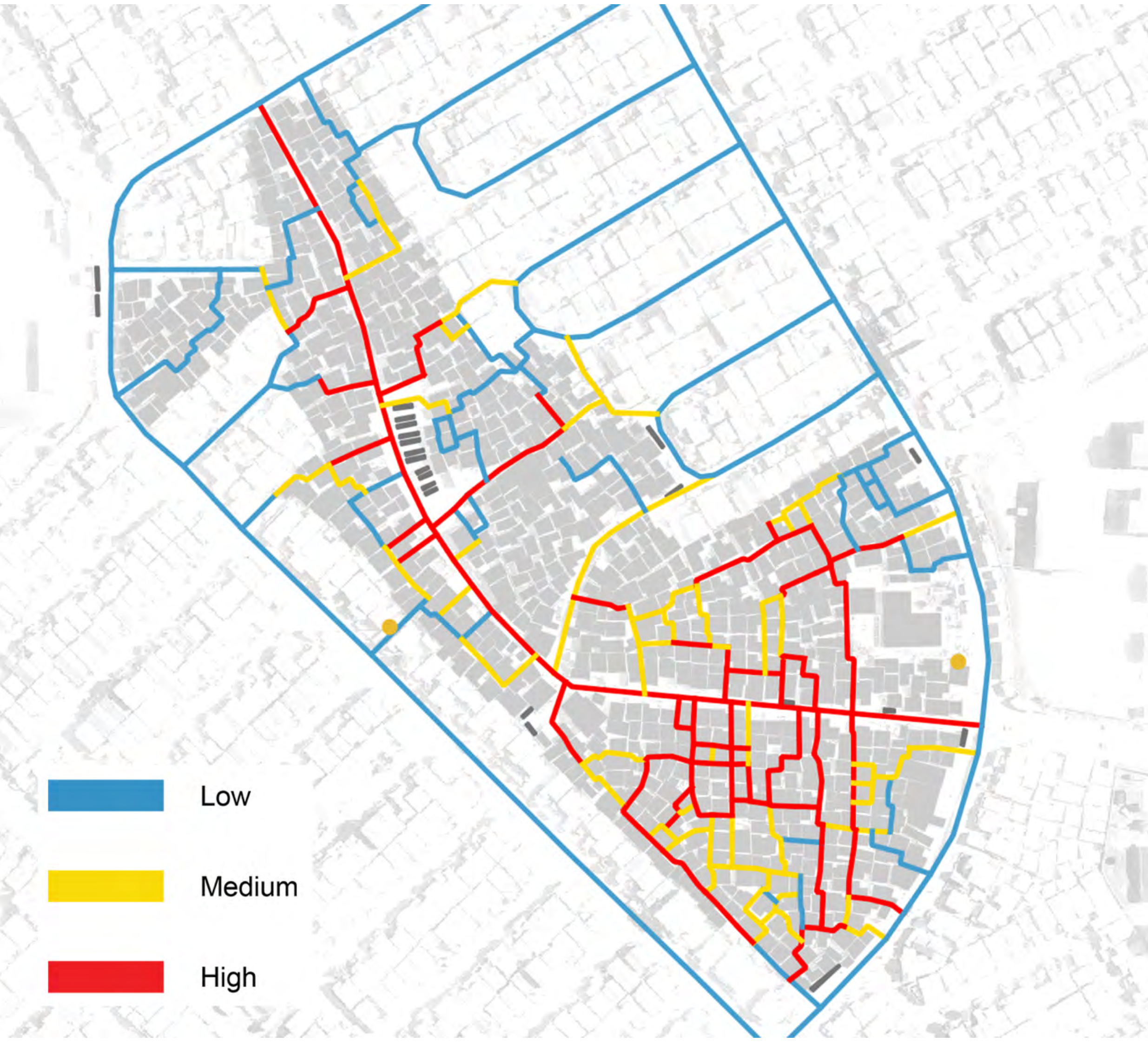
Statistic	N	Mean	St. Dev.	Min	Max
Shortest Paths					
Spaza Count	78	34.77	48.59	0.167	247.25
Central Street Entrance Count	78	30.34	49.80	0.00	366.00
C Section Entrance Count	78	31.03	40.27	0.00	206.00
Total Count	78	96.14	111.41	0.50	562.50
Avg. Count	78	32.05	37.14	0.17	187.50
Space Syntax					
Avg. Choice (radius = 150 m)	78	2,080.23	2365.16	101.50	10,645.00
Avg. Choice (radius = *n*)	78	6,403.55	7,420.59	40.00	31,701.33
Normalized Choice (radius = 150 m)	78	3.32	0.44	2.01	4.03
Normalized Choice (radius = *n*)	78	3.51	0.57	1.63	4.50

Figure 3. Most used paths under the shortest-paths framework



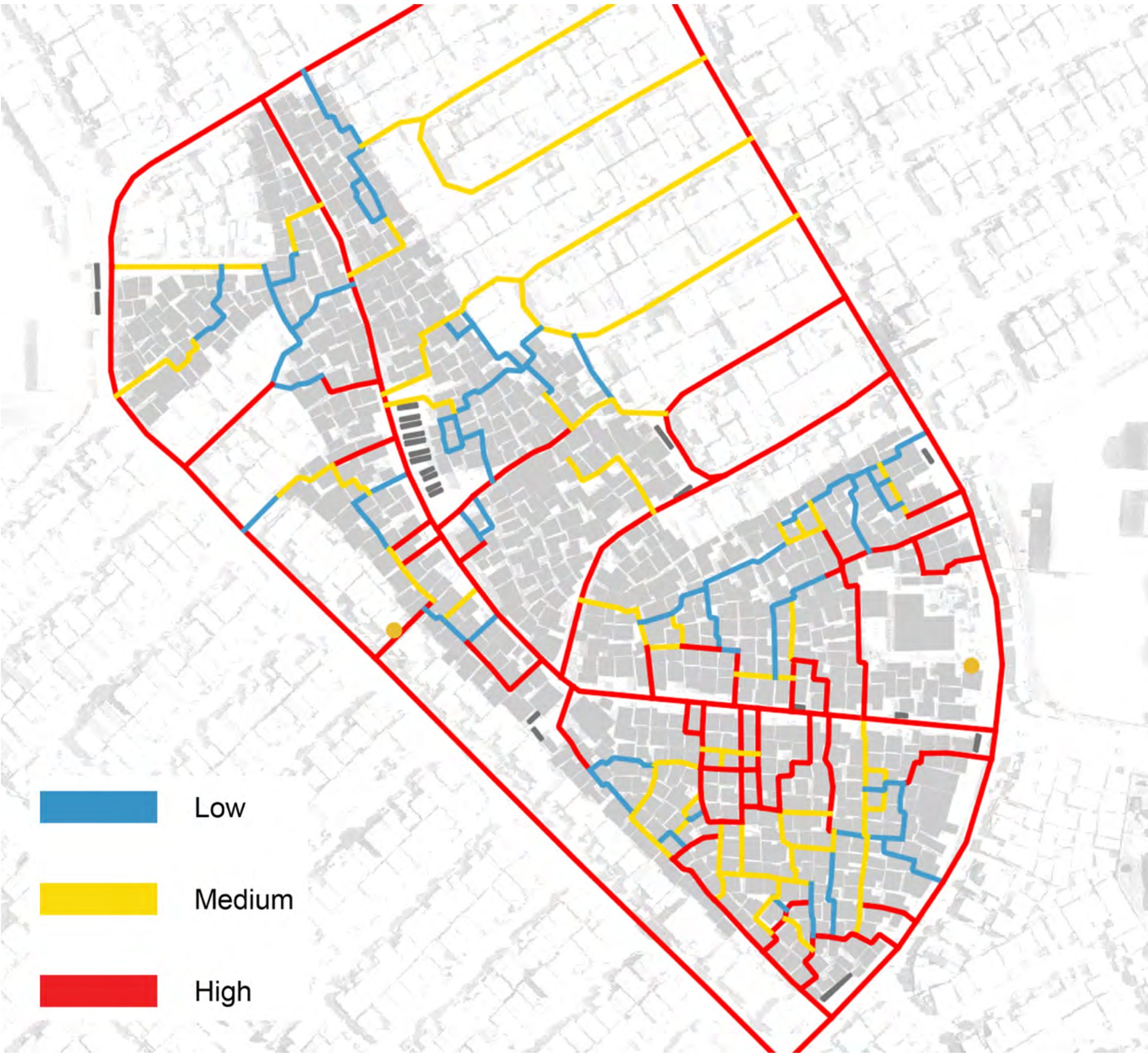
All three shortest path scenarios have been summed to reveal the combined most used routes.

Figure 4. Normalized angular choice (radius = 150 m)



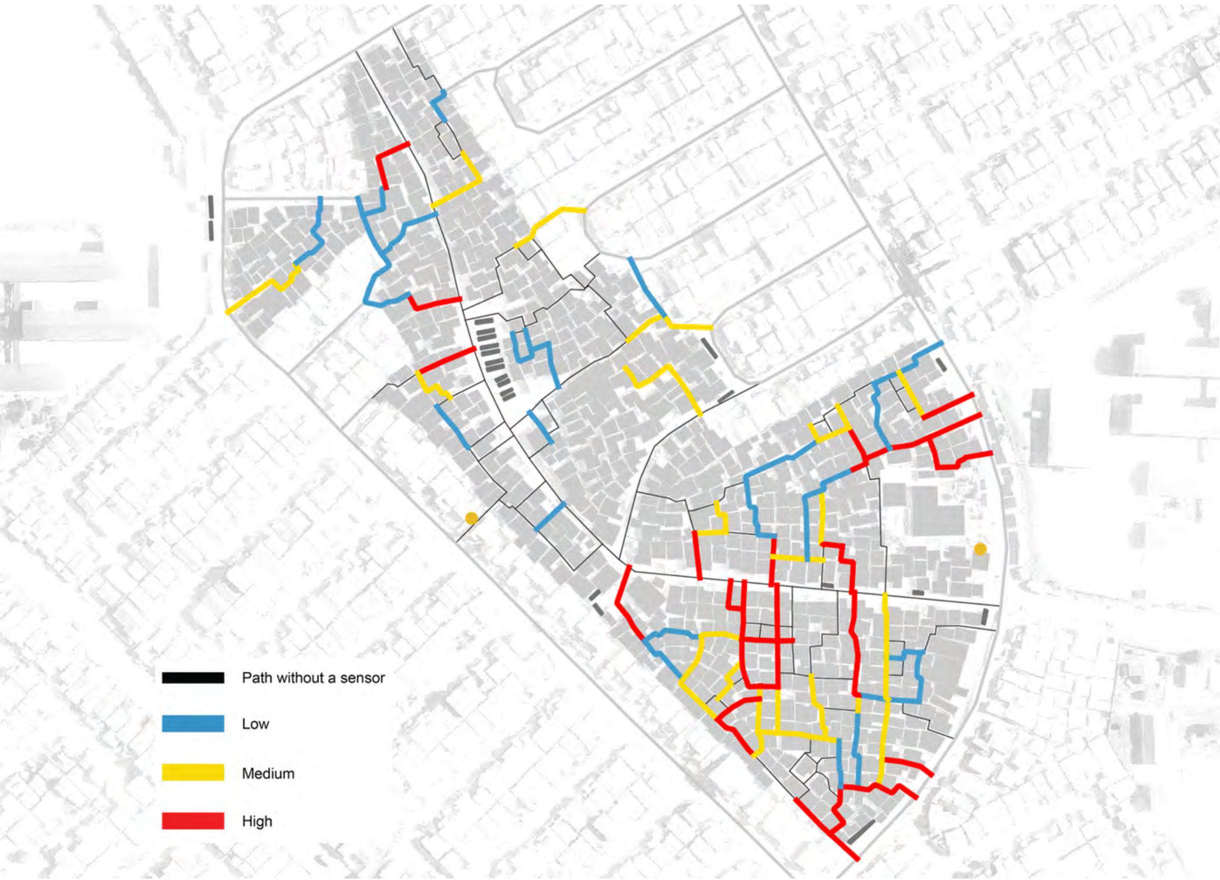
The map shows the distribution of pedestrian activity in the informal settlement including the surrounding area with a radius of 150 meters. Low ranges from 0.9 – 3, medium from 3 – 3.5, and high from 4.5 – 4.28.

Figure 5. Normalized angular choice (radius = *n*)



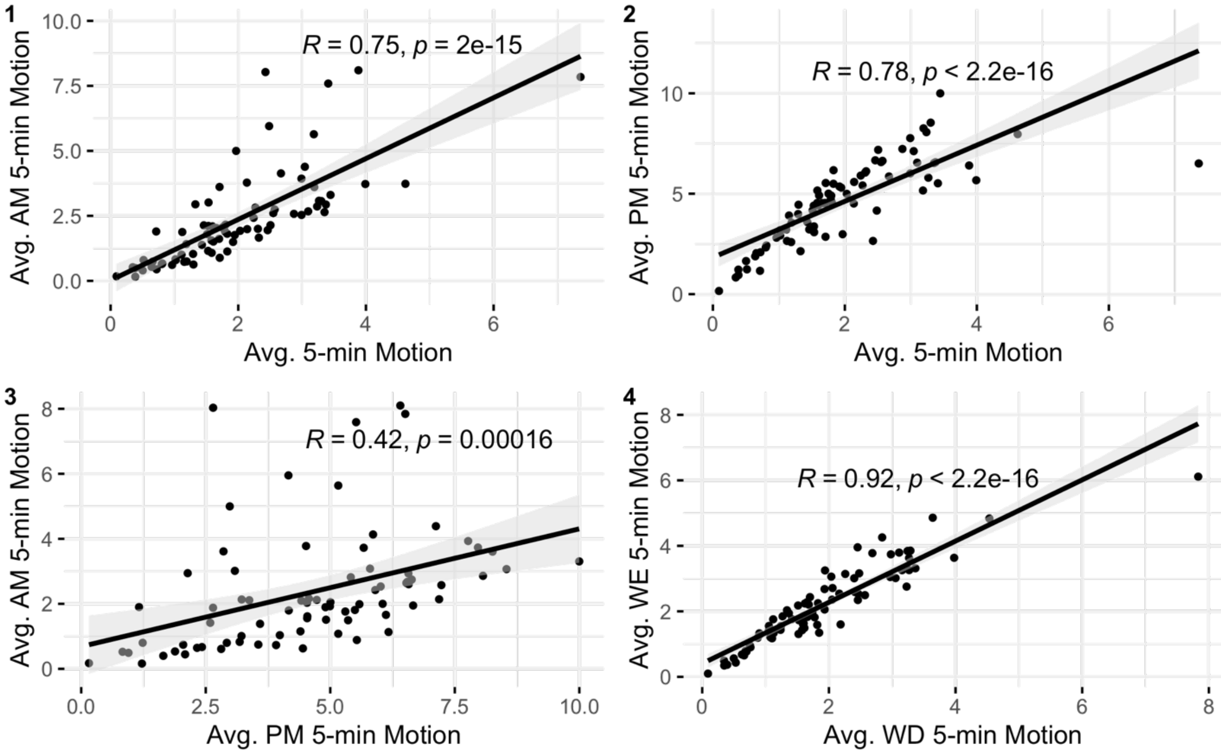
The map shows the distribution of pedestrian activity in the informal settlement including the surrounding area with a radius of *n*. Low ranges from 0.3 – 3.17, medium from 3.17 – 3.78, and high from 3.78 – 4.56.

Figure 6. Mapped values for normalized angular choice (radius = *n*) on sensor-monitored paths



The map shows the distribution of pedestrian activity in the informal settlement on paths for which there is sensor data during the study period.

Figure 7. Correlation between sensor data time periods



Correlation between average five-minute motion (all hours) and average five-minute morning motion (1), all-hours average motion and average five-minute evening motion (2), average evening and morning motion (4), and average weekday five-minute motion and average weekend five-minute motion (4). The solid line (in this and all following correlation plots) represents the ordinary least squares regression line with 95% confidence intervals represented in light gray.

Figure 8. Correlation between average five-minute motion (6:00 pm – 8:00am) and theory-driven calculations

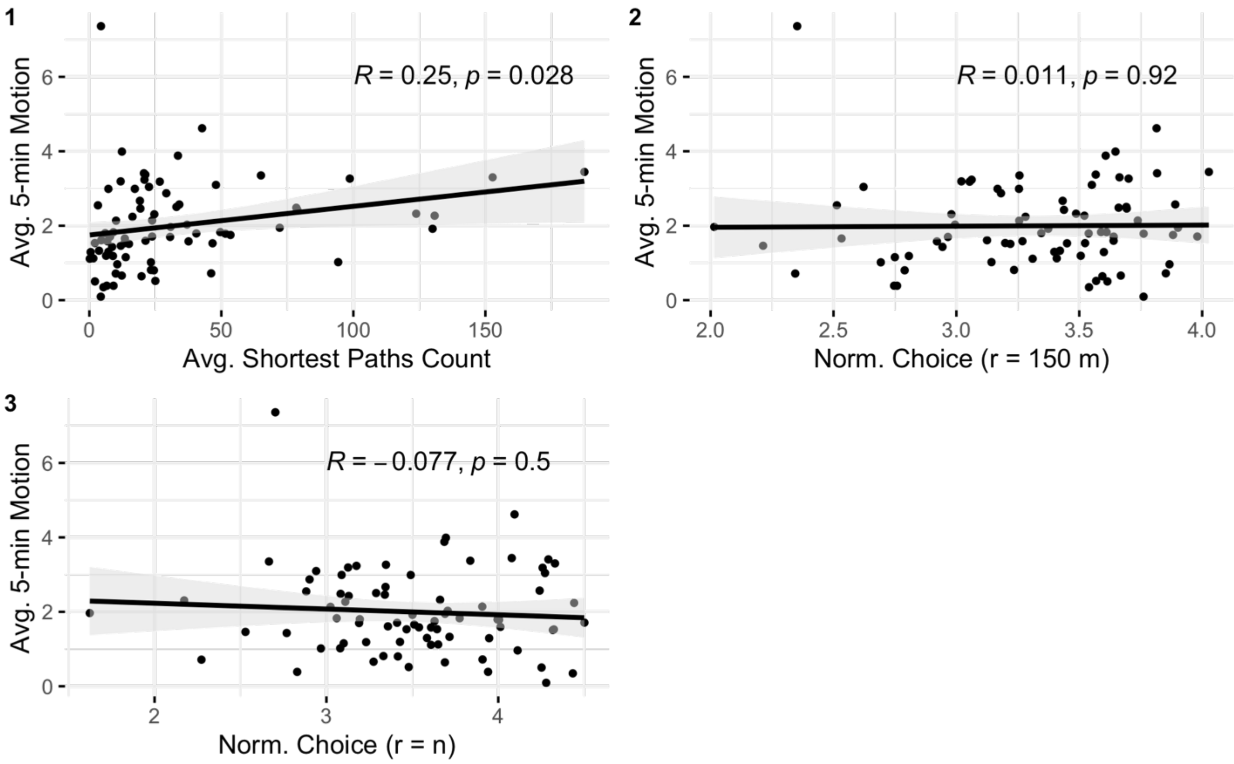


Figure 9. Correlation between average evening (6:00 – 9:00 pm) five-minute motion and theory-driven calculations

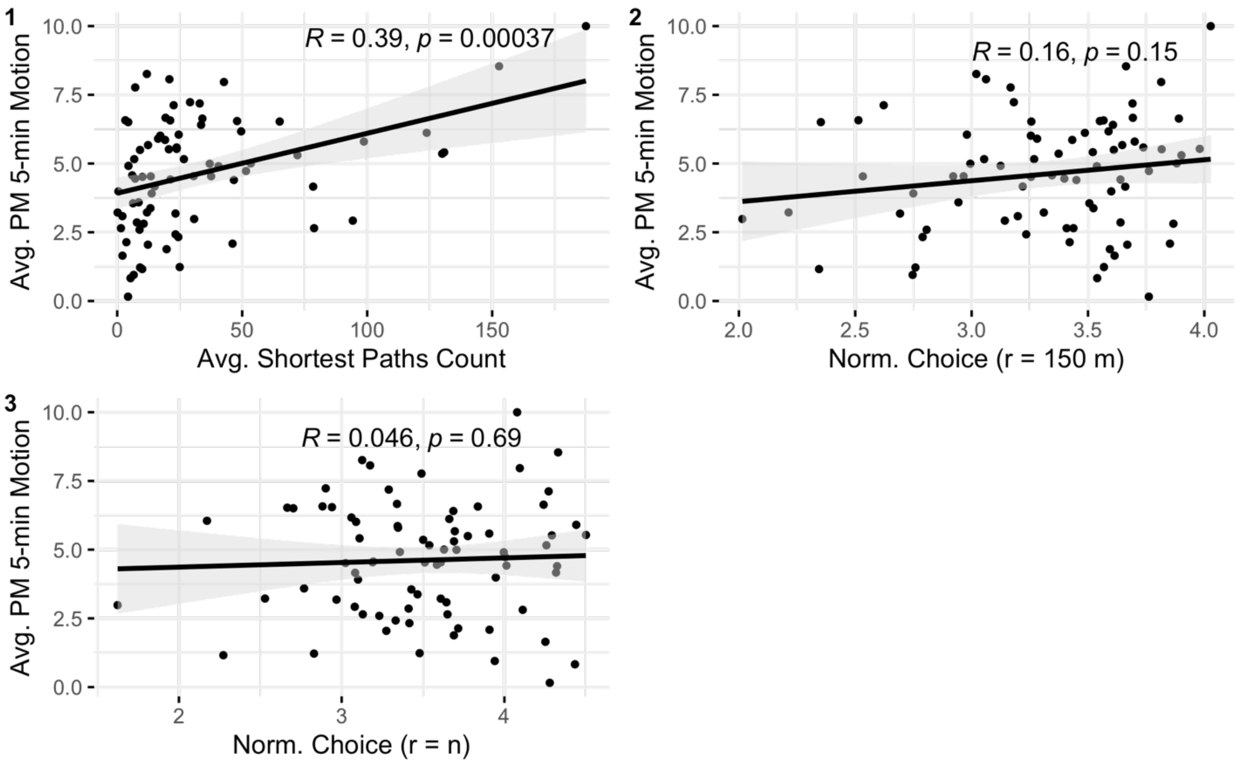


Figure 10. Correlation between average morning (5:00 – 8:00 pm) five-minute motion and theory-driven calculations

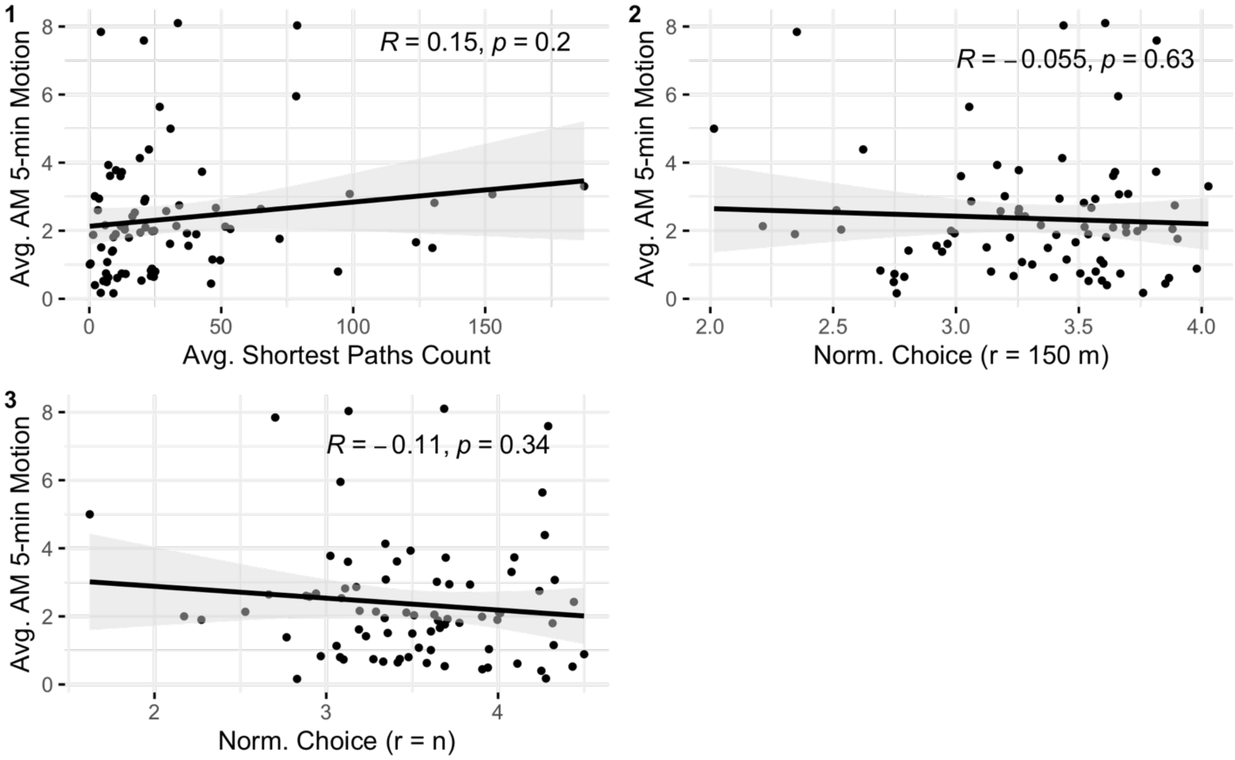


Figure 11. Correlation between average weekday (Mon – Fri) five-minute motion and theory-driven calculations

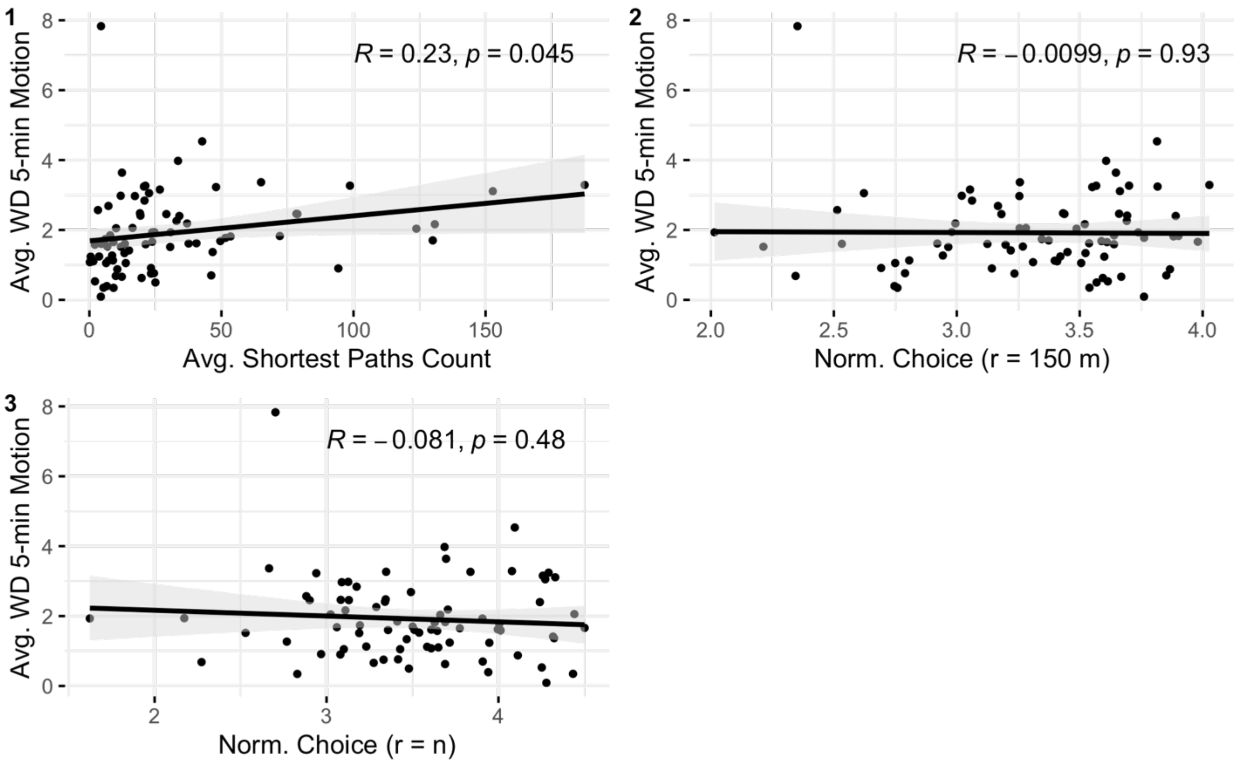
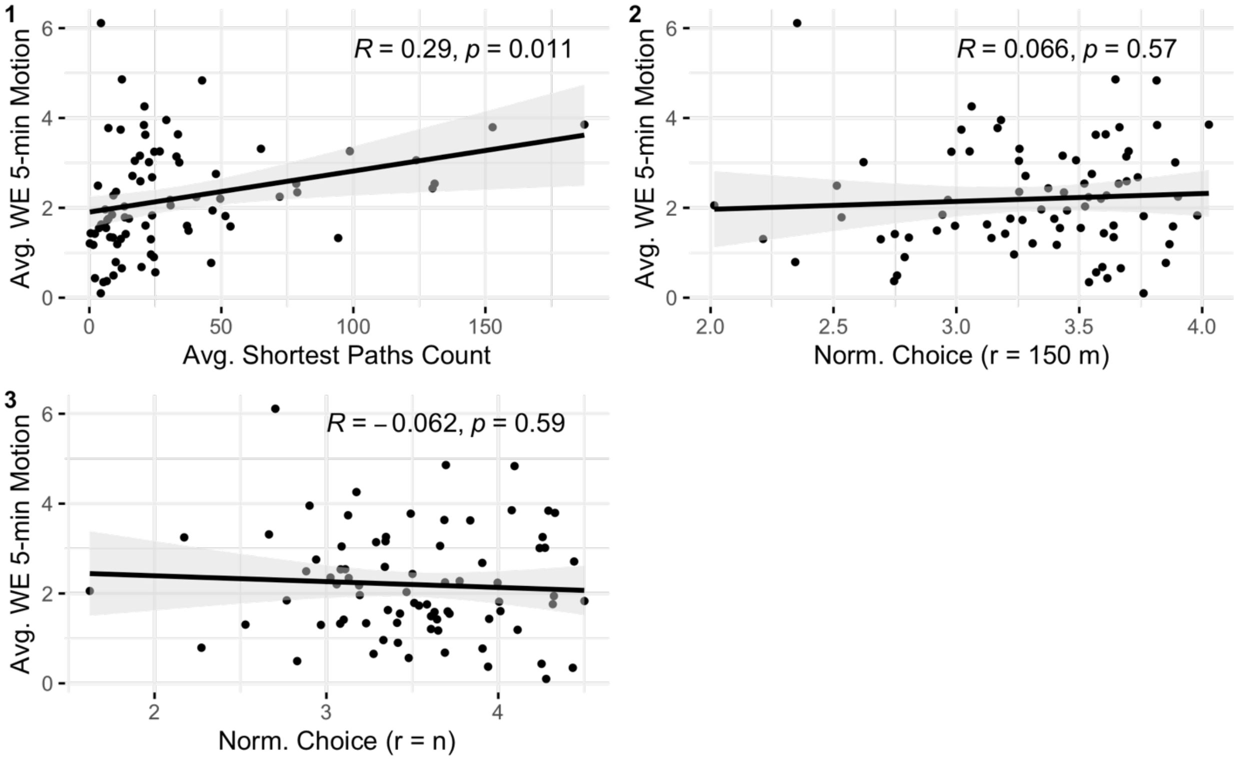


Figure 12. Correlation between average weekend (Sat/Sun) five-minute motion and theory-driven calculations



ARTICLE 2: **MOBILITY IN INFORMAL SETTLEMENTS DURING A PUBLIC LOCKDOWN — A CASE STUDY IN SOUTH AFRICA**

Status: Submitted to PLOS ONE — Revise and Resubmit

Authors: Yael Borofsky and Isabel Günther

1. INTRODUCTION AND BACKGROUND

As COVID-19 spread early in 2020, African countries were among the quickest to follow World Health Organization (WHO) guidelines and impose strict lockdowns to limit mobility as well as most social interactions, even though many countries still had fewer than 100 cases at the time. South Africa, in particular, instated one of the strictest lockdowns in the world (Hale et al., 2020). Despite the rapid response, many academics and thought leaders of civil society were almost as quick to point out that with so many low-income, dense informal settlements in cities throughout Africa, lockdowns may be, at best, impractical and infeasible and, at worst, more devastating than COVID-19, itself (Austrian et al., 2020; Bargain & Aminjonov, 2020; Barnett-Howell & Mobarak, 2020; Chibwana, 2020; Duflo & Banerjee, 2020; Durizzo et al., 2020; Lashitew, 2020; Nyashanu et al., 2020; Ravallion, 2020; Robalino, 2020).

To better understand this concern, we analyze data from novel, nighttime pedestrian motion sensors (Appendix B Figure 1), which were installed in an informal settlement as part of a pre-existing study in Cape Town, South Africa. We analyze whether widespread concerns about non-compliance with curfew regulations in informal settlements are reflected in motion at night in this informal settlement.

Since roughly one in seven people worldwide live in informal settlements, knowing more about the feasibility of lockdowns and compliance with mobility restrictions in these neighborhoods is critical in a pandemic (Dodman et al., 2018). We use the term "informal settlement," rather than "slum," since "slum" can have a derogatory connotation (2020). There are several elements of life in these neighborhoods that make social distancing, let alone lockdowns of social and economic life, problematic (Corburn et al., 2020; Wilkinson et al., 2020). While informal settlements vary in terms of physical form, size, and infrastructure access, one major characteristic is that water and sanitation infrastructure are typically shared. Without access to private water and sanitation, people have to go out multiple times per day, making it impossible to follow strict curfews and avoid contact with non-household members.

Density is another major concern. While the number of household members sharing a living space varies, most informal homes are small. In the informal settlement we study, rooms are typically shared. With little indoor or private outdoor space, households do many daily activities, such as laundry, in public or semi-public spaces, such as directly in pathways or in the shared spaces between homes.

The third major concern is economic. Many people living in informal settlements are low-wage earners in the informal sector, such as day workers or domestic workers, with little job security or social protection and small savings. Asking these people not to work often means asking them to forego income they need to purchase even basic necessities. For example, one survey of 19,000 South Africans finds that within two weeks of lockdown, two thirds of respondents living in poor, urban areas did not have enough money for food (HSRC, 2020). It is unrealistic to expect that people living in this precarious situation will not continue to search for and travel to available work.

As a result, many researchers, NGOs, and health care providers worried that residents in informal settlements were not reducing mobility and social contact in response to restrictions, which are essential to limit the spread of COVID-19 (in the absence of a vaccine) and other future highly infectious diseases. Several media reports from South Africa depicted residents of informal settlements outdoors, sometimes without masks or in close proximity to others, when the law stipulates that everyone must be inside (News24, 2020; Trenchard, 2020). Two hypotheses have emerged from this discourse to explain how curfews might affect the behavior of residents and the spread of COVID-19 in low-income neighborhoods. First, the "higher mobility" hypothesis is that lockdowns have less of an impact on mobility in lower-income communities either because low-income people are more likely be essential workers, less likely to have the option of working remotely, less likely to have the financial capacity to stay home without working, or less likely to comply with lockdowns for other reasons. Second, the "crowded housing" hypothesis argues that dense housing and shared essential service infrastructure create an environment conducive to the spread of COVID-19 (Sheng et al., 2021).

In response to these explanations, a rapidly growing body of literature seeks to better understand behavioral responses to the state-mandated lockdowns in lower-income countries, especially in urban areas, with mixed results. For example, phone survey data has provided some insight into self-reported activity patterns (Austrian et al., 2020; Durizzo et al., 2020; HSRC, 2020; Nyadera & Onditi, 2020; Nyashanu et al., 2020; Parikh et al., 2020; Pinchoff et al., 2021). In a survey of more than 1,400 low-income, urban residents in Johannesburg and Accra conducted in April 2020, Durizzo et al. (2020) find that 25-40% of people still report attending large gatherings and 10-20% report receiving guests at home. In contrast, a survey (N = 19,000) in South Africa run by the Human Sciences Research Council (2020) finds that almost everyone reports complying with lockdown restrictions (staying home or only leaving for essentials). One study in Nairobi, Kenya targeting residents of informal settlements (N = 2,009) conducted early in the pandemic, finds that while almost all participants report staying home more, fears about income loss and food shortages are the main reason why respondents report that measures like quarantines or self-isolation would not be feasible (Austrian et al., 2020).

In addition to self-report data for lower-income countries, many studies draw on large-scale data from Google, Apple, or nationally available mobile phone data to study mobility changes in response to lockdowns in higher-income countries. See, e.g., for the US: Chang et al. (2020), Warren & Skillman (2020), Engle et al. (2020), Klein et al. (2020), Cronin & Evans (2020), Coven & Gupta (2020), Lee et al (2020); for Italy: Pepe et al. (2020); for France: Pullano (2020); for the UK: Jeffrey et al. (2020); for Spain: Aloi et al. (2020); for Brazil: Queiroz et al (2020); for India: Sheng et al (2021); Multiple countries: Bharati & Fakir (2020), Yilmazkuday (2020), Bargain & Aminjonov (2020). These studies overwhelmingly document mobility declines in response to both the pandemic, in general, and lockdowns specifically, with declines as high as 50-70% in March 2020. A few studies use Google Mobility data to analyze lower-income countries (Bargain & Aminjonov, 2020; Bharati & Fakir, 2020; Yilmazkuday, 2020). Bharati & Fakir (2020) find that stricter lockdowns in poorer countries reduce mobility more than in richer ones. In contrast, Bargain & Aminjonov (2020) find that mobility for work decreases less in lower-income areas than in higher-income ones, while other activities show less of a discrepancy between richer and poorer areas. Last, three studies use mobile phone tracking apps to measure mobility in response to the lockdown. Two research groups (Intervista, 2020; Molloy et al., 2020) each find a roughly 70% decrease in average daily distance (km) after lockdown began on March 16. The third study, in rural Thailand, found mobility decreased by 90% (Haddawy et al., 2021).

Yet, to our knowledge, only one other study tries to measure mobility among residents from informal settlements in response to the global lockdown (Sheng et al., 2021). Using phone location data in Mumbai India, Sheng et al. (2021) find little difference in the level of mobility between residents of informal settlements and those living in formal areas. Yet, they do not study mobility patterns within informal settlements, but rather the movement of residents out into the broader area.

This difference is important since individuals living in informal settlements may not necessarily be well represented in Google Mobility (or other types of phone) data (Bargain & Aminjonov, 2020; Bharati & Fakir, 2020; Sheng et al., 2021). First, as Sheng et al. (2021) observe in Mumbai informal settlements, mobile phones are often shared. Second, in our setting, pre-paid cellular data is expensive and residents often switch off cellular data to control usage, only purchase WhatsApp data, or go for stretches with none at all. Third, mobility tracking apps are limited by GPS accuracy, making it hard to identify tracks within dense, informal neighborhoods.

We contribute a unique, hyper-local perspective to the growing number of studies on the impact of government lockdowns on mobility in a particularly difficult-to-study context — informal settlements. We use data from previously-installed nighttime pedestrian motion sensors in an informal settlement in Cape Town with about 2,300 residents (as of 2019) to analyze how nighttime activity patterns changed in response to South Africa's lockdown, which began on March 27, 2020. Rather than tracking individuals, the sensors measure activity frequency (pedestrian count) in the areas where they are installed. Our data suggest that residents seem to comply with lockdown restrictions as much as possible, though not perfectly, and that many seem to have already reduced mobility in the weeks prior to the official lockdown, around when the first COVID-19 cases were reported in South Africa and a state of disaster was announced.

2. CONTEXT OF STUDY SITE

The informal settlement we study is one of approximately 450 in the City of Cape Town, the second largest city in South Africa (we do not disclose the name due to ethical concerns) (Ndifuna et al., n.d.). This thirty-year old informal settlement is home to approximately 2,300 residents and is located in a township called Khayelitsha, which was zoned as Black African under apartheid.

South Africa has had one of the most severe COVID-19 outbreaks in Africa (Daniel et al., 2020; Worldometer, 2020) and also instated one of the strictest lockdowns in the world in response to the first wave of the virus (Hale et al., 2020). The first known case of COVID-19 was confirmed on March 3, 2020 in KwaZulu Natal and announced on March 5, 2020 (Department of Health, 2020a). On March 11th, the WHO formally announced that the COVID-19 outbreak constituted a pandemic (WHO, 2020). On the same day, authorities confirmed the first case in the City of Cape Town, a city of approximately four million people, bringing the total number of cases in the country to 13. No mobility restrictions were yet recommended in Cape Town (Department of Health, 2020b; Western Cape Provincial Government, 2020).

On March 15, 2020, President Cyril Ramaphosa announced a national state of disaster. The country had 61 confirmed COVID-19 cases, some due to community transmission. President Ramaphosa implemented a travel ban on foreign nationals from high-risk countries, shut down 35 of 53 land ports and two sea ports, prohibited gatherings of 100 or more people, cancelled celebrations of upcoming national holidays, ordered schools to close on March 18, 2020, suspended visits to correctional facilities, called on businesses to put hygiene control measures in place, prohibited liquor sales after 6:00 pm, and limited the capacity of alcohol establishments (Department of Cooperative Governance, 2020; Ramaphosa, 2020). This announcement represented the first substantive call from the South African government for citizens to practice social distancing.

By March 21st, the Western Cape Premier Alan Winde announced 74 confirmed COVID-19 cases in the Western Cape, the province that includes Cape Town, and began directly encouraging people to stay home if possible and maintain a 1.5 meter distance from others in public (Western Cape Office of the Premier, 2020). By March 23, 2020, when President Ramaphosa announced a nationwide lockdown to start on March 27, the country had 402 confirmed cases (Ramaphosa, 2020). Between March 27, 2020 and April 30, 2020, South Africa implemented what became known as a Level 5 lockdown – one of the strictest in the world (see Appendix B Figure 3). South Africans were not allowed to leave home unless they were essential workers, were going out to purchase essentials, like food and medicine, or were seeking healthcare, banking services, or government aid. On May 1st, South Africa moved from Level 5 to Level 4 lockdown, in which residents were allowed to go out from 6:00 am - 9:00 am for recreation and an 8:00 pm to 5:00 am curfew was in effect. Level 3 began on June 1, 2020 and involved re-opening South Africa's economy along with a relaxation of the limits on non-essential outdoor activity. Alcohol purchased for home consumption was allowed again. Gatherings (and funerals of more than 50 people) as well as activities that involved large gatherings of people remained prohibited.

All Level 5 and 4 (March 27 until May 31, 2020) lockdown regulations could affect movement patterns, however, certain patterns were unlikely to change. Residents of informal settlements in South Africa, including the settlement we study, often share water and sanitation facilities, meaning that it would be nearly impossible to have perfect compliance with any curfew. People who became unemployed were no longer commuting. Thus, expected activity peaks during the morning and evening commuting period should be drastically lower. On the other hand, more unemployed people could also mean crowded households and thus, people may step out more at any hour to get fresh air or take a break from other household members. Durizzo et al. (2020), for example, find that 17% of South Africans in their sample report that living in a crowded or single-room home is an obstacle to following lockdown regulations.

3. DATA AND METHOD

As part of a pre-existing study, we installed 171 PIR sensors on 121 paths[16] and 50 private or semi-private shared compounds (like courtyards or cul-de-sacs) throughout an informal settlement in February 2020. When fieldwork for the original project was interrupted in March 2020 by the COVID-19 pandemic, these sensors remained in place, passively gathering motion data. Working individually, our field team collected these data using Bluetooth-enabled mobile phones during the three-hour window in which South Africans were permitted to be outdoors for non-essential purposes (Level 4).

The sensors were developed in collaboration with Sensen[17], a company that builds dataloggers for international development projects. The PIR sensor detects differentials in thermal radiation, which trigger the device to record a count (Appendix B Figure 1). Every five minutes the sensor saves the trigger count in that five-minute period, recording no other information about

[16] These numbers differ from those reported in Article 1 because in January 2020 the data collectors requested one sensor be removed from a location where they felt it was extremely likely to be stolen.

[17] More information about Sensen can be found here: http://www.sensen.co/

passersby. Thus, our dataset includes a count for every five-minute period of each day that the sensors are installed, activated, and functional. The sensitivity of the PIR sensor prevents it from accurately measuring motion during the day, when heat created by the building materials common in Cape Town's informal settlements (e.g., zinc or corrugated iron) causes false triggers. Therefore, we only study activity between 6:00 pm – 8:00 am.

Unfortunately, sensor attrition was a problem, since dysfunctional sensors could not be repaired or replaced during the lockdown. The most common reasons for sensor attrition were battery discharge and vandalism/theft. Under normal circumstances our team can recharge batteries, however, under lockdown the restrictions on outdoor activities as well as health concerns for the field staff prevented maintenance. In addition, several sensors were stolen or damaged at the end of May. We removed all remaining sensors between June 19 – 20 in order to save them for the original study they were intended for (on hold due to the pandemic).

Using data from sensors that were active throughout the study period, we have 60 sensors in paths and 26 sensors in compounds. We study changes in activity in response to the evolving COVID-19 pandemic in South Africa, and in response to both the Level 5 and Level 4 lockdowns between 6:00 pm and 8:00 am for the three-month period from February 14 – May 14, 2020. If we include all data until June 18, 2020 (the day before we began removing sensors), we have data from 21 path sensors and 18 compound sensors.

Since data is transmitted via Bluetooth, some observations can be lost during the transfer if the signal fails. Since this loss is generally random, we include a sensor as long as there are at least 69 days of data (~93% of days) and the missing days are not clumped at the end of the study period (indicating battery discharge, not random loss). Hence, our data cover six weeks before the lockdown started on March 27, seven weeks under full restrictions (Level 5), and two weeks where recreation was allowed between 6:00 am – 9:00 am (Level 4). The extended dataset with fewer sensors includes all of Level 4 (four weeks) and three weeks of Level 3, when most movement restrictions were lifted, but gathering restrictions were still in place.

To detect changes in nighttime motion over time, we first compare average activity across all weeks beginning on Feb. 14, 2020 and average activity across the different stages of lockdowns (Levels 5, 4, and 3). Moreover, to detect the drivers of changes in motion in the weeks during the lockdown in comparison to the weeks before, we compare average nighttime activity before and after March 27, 2020 for different days of the week and different times of the evening, night, and early morning by estimating equation (1):

$$Activity_{it} = \beta_0 + \beta_1 LOCKDOWN_t + \beta_2 \theta_t + \beta_3 (LOCKDOWN_t \times \theta_t) + \alpha_i + \varepsilon_{it} \quad (1)$$

Where $Activity_{it}$ is the average five-minute motion or trigger count on path/compound i at time t, θ_t is a vector of dummy variables, one for each day of the week (or hour of the night for the second regression). $LOCKDOWN_t$ is coded as 1 beginning at midnight on March 27, 2020 and afterward, and is coded as 0 before. We run all specifications with and without sensor fixed effects, where α_i refers to sensor fixed effects. ε_{it} is the robust standard error term. β_1 indicates the change in five-minute motion after the onset of South Africa's lockdown compared to average nighttime activity before. β_2 is the average change in five-minute motion for day of the week (or hour of the night) compared to the constant. β_3 shows the interaction effect of $LOCKDOWN_t$ and the unit of time θ_t (day or the week or hour of the night). To check if there is a statistically significant difference between average activity during Level 5 compared to Level 4 and Level 4 compared to Level 3, we use a Welch's Two-sample *t*-test of difference in means. All analysis is conducted using R Version 4.0.4.

After a first quantitative analysis, we conducted qualitative semi-structured interviews in October 2020 with four members of our local field team to contextualize the results. We presented figures depicting the main findings to the team members and asked open-ended questions about their observations of life under lockdown with respect to the units of time we analyze. The initial study using the sensors was approved by the Ethics Commission of ETH Zurich (EK 2019-N-19) and an extended approval for this study was granted in August 2020.

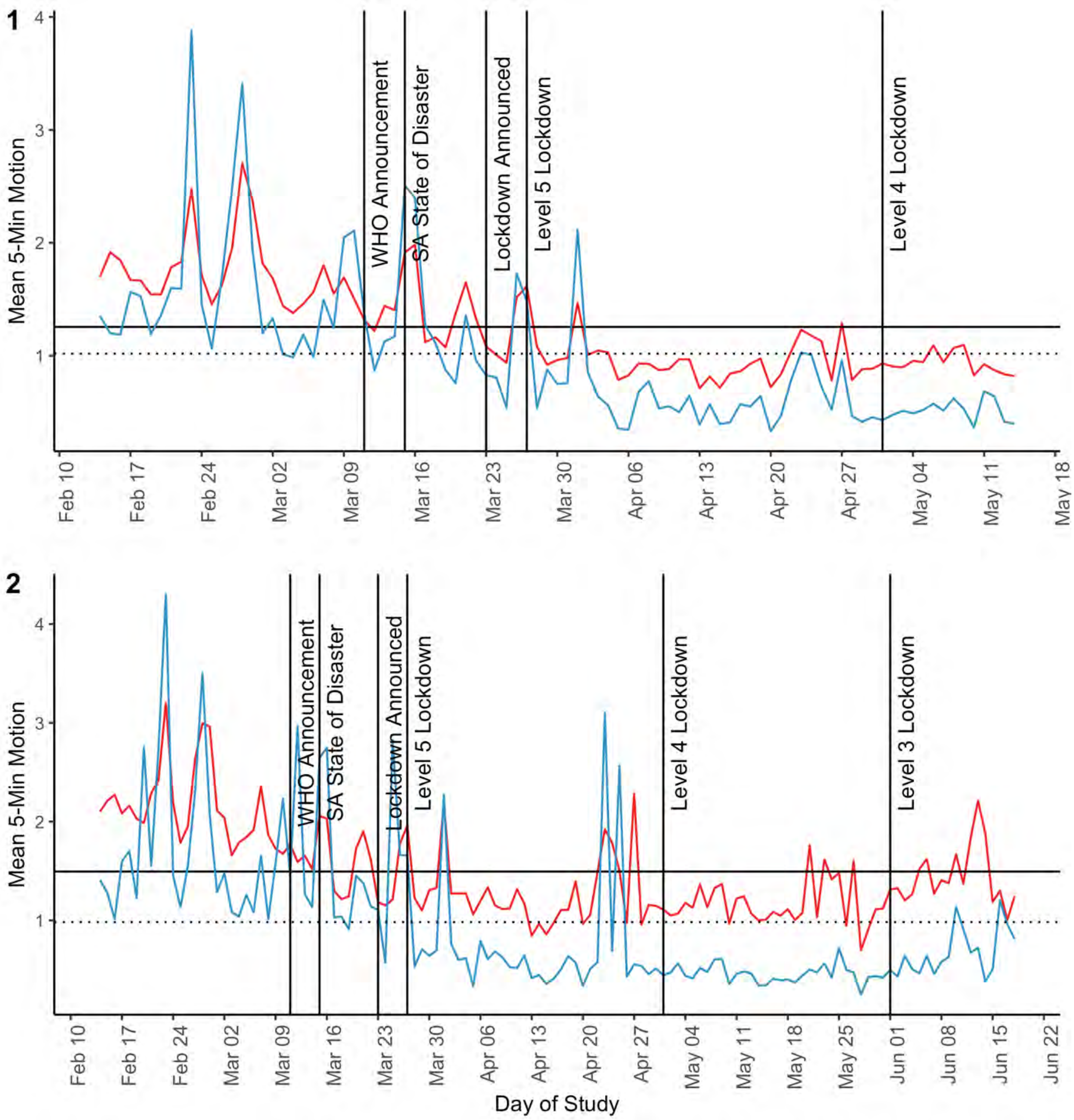
4. RESULTS

4.1 IMPACT OF LOCKDOWN ON MOBILITY

Over the entire study period from February 14 – May 14, 2020, the average five-minute motion between 6:00 pm – 8:00 am was 1.25 triggers per five-minute period on paths (*sd:* 2.72) and 1.02 triggers per five-minute period in compounds (*sd:* 3.2) — about 15 per hour in paths and 12.2 per hour in compounds. We analyze path and compound sensors separately, since they measure different types of activity. Sensors on paths generally measure people in transit, while sensors installed in compounds measure the activity of a few people in a small space.

From pure visual inspection of Figure 1, which tracks the daily five-minute mean throughout the study, we see a steady decline in motion already at the beginning of March (before the national lockdown). Notably, that decline bottoms out and flattens shortly after South Africa implements an official lockdown on March 27, 2020. Moreover, the activity peaks associated with weekends visible in February, and to a slightly lesser extent in March, largely disappear in April (Level 5) and May (Level 4). Although some restrictions on morning activity were lifted in Level 4 and more people could potentially work, activity remains low. With Level 3, activity in June (Figure 1, Panel 1) rises again, consistent with the loosening of many restrictions, but mobility remained lower than in February before the first COVID-19 cases occurred. In Figure 1, the bottom panel shows means from sensors that worked until Level 3. Although the pattern is less smooth, due to greater variance, it is very similar to the top panel, where more sensors are included.

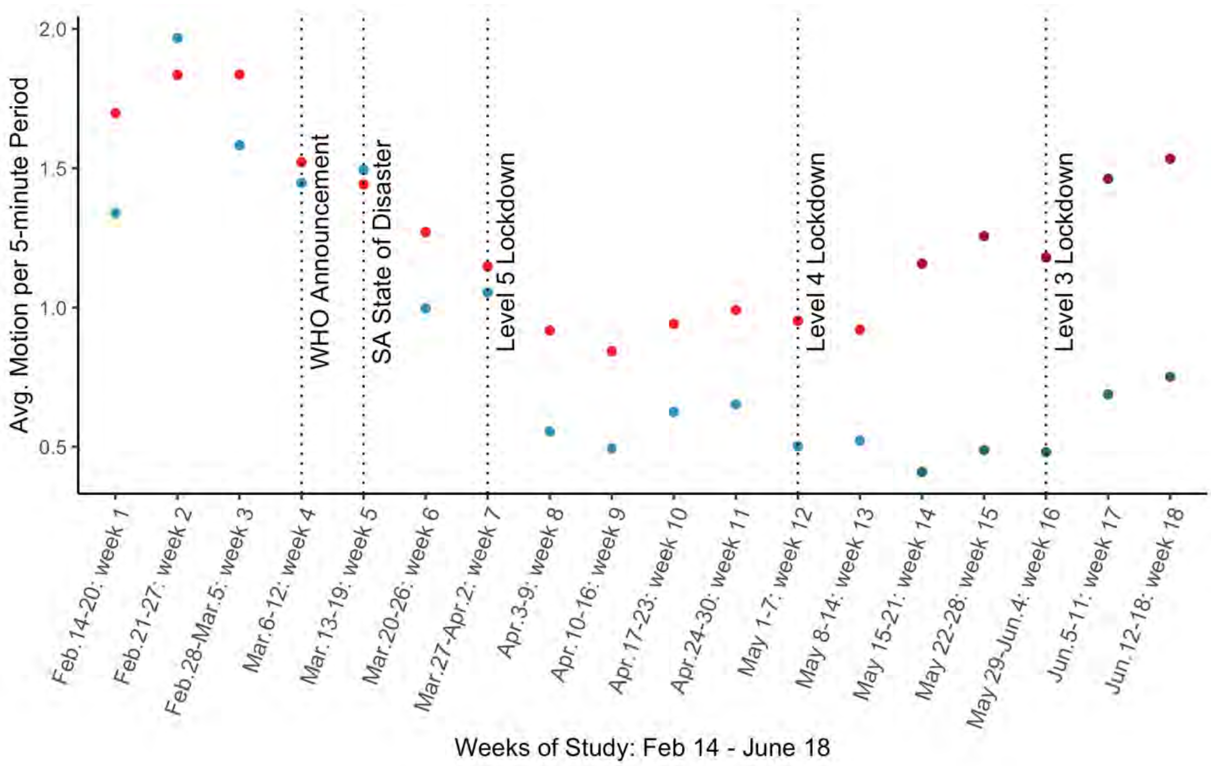
Figure 1. Average five-minute motion over the study period



The figures plot the average five-minute motion for each day of the study (Panel 1: Feb 14 – May 14; Panel 2: Feb 14 – June 18). The x-axis shows the date on every Monday. The red line represents data from sensors installed in paths (Panel 1: 60; Panel 2: 21), while the blue line represents data from sensors installed in compounds (Panel 1: 26; Panel 2: 18). The black horizontal line is overall five-minute path average and the dotted black line is the overall five-minute compound average.

If we look at week-to-week changes in average nighttime activity (Figure 2), the change in average motion is significant throughout the study period. We find that in the paths (red dots), nighttime motion steadily and significantly declines between February 28 and March 26 (23% in weeks 4 – 6, Figure 2, Appendix B Table 1) — the three weeks before the lockdown. Compound nighttime motion (blue dots) is more erratic in the month prior to lockdown. Still, an overall decline (19% in weeks 4 – 6) in March is evident (Figure 2, Appendix B Table 1).

Figure 2. Average five-minute motion by week of the study



The plot shows mean five-minute motion by week of the study. Red points represent path means; blue points represent compound means. Underlying data is the same as in Figure 1. Dark red and dark blue points indicate means from the restricted dataset that adds weeks 14 –18 to the study period. Means in the restricted dataset prior to week 14 are generally similar, but the pattern is a bit noisier. The coefficient is significant in each week in the main study period (weeks 1 – 13) for both paths and compounds (Appendix B Table 1). For a version of this graph with only data from the restricted dataset see Appendix B Figure 2.

In week 7, the first week of lockdown, the decline in average five-minute motion in paths seems to follow the pattern, with a similar decline in mean motion between week 6 and week 7, but in the second week of lockdown (week 8: Apr. 3 – 9) average five-minute motion drops sharply below one trigger per five-minute period. Weeks 9 – 11 (Level 5) remain relatively stable (Appendix B Table 1, column 1). Also, in the first two weeks of Level 4 (weeks 12 and 13), when more outdoor activities were allowed again, outdoor mobility remained low.

To see how nighttime activity evolved over the extended study timeline, we show average weekly five-minute motion in Figure 2 for weeks 14 – 18 from the smaller sample of sensors. By weeks 17 and 18, the second and third week of Level 3, we already see nighttime activity levels in paths have returned to levels similar to weeks 5 – 7 (just before and at the start of Level 5). If we compare the means for weeks 16 – 18 from the extended data to the means for weeks 5 – 7 from the main data, the means are practically similar enough to indicate a return to pre-lockdown nighttime activity (Appendix B Table 1, column 3), but not to "normal" outdoor activity (weeks 1 – 3).

Compound nighttime motion follows a similar pattern to paths, however, activity dropped more slowly in compounds than in paths before the lockdown, but then more drastically once lockdown was announced. Moreover, nighttime activity also seems to rebound for compounds when Level 3 was announced, but does not — in contrast to paths — come close to pre-lockdown levels. Again, comparing weeks 5 – 7 from the main dataset to weeks 16 – 18 from the extended dataset, respectively, the five-minute means in June are only half as large as the three weeks prior to lockdown in March.

When we compare mean five-minute motion during February 2020 to mean motion during lockdown (March 27 – May 14, 2020), we find that five-minute motion decreased by 48% in paths. Compared with the entire pre-lockdown period in our study (February 14 – March 26, 2020), on average, the lockdown is associated with a 40% decrease in path pedestrian triggers per five-minute period during the lockdown ($p < 0.01$), bringing the mean number of pedestrians from 1.6 per five-minute period to 0.96 per five-minute period. In other words, on average, prior to the lockdown sensors measured about 19 triggers per hour, while after lockdown the total was about 11.5 triggers per hour (Appendix B Table 2, column 1). Then, using results from Appendix B Table 1 (column 1), we can separate out the effect of activity declines in March, when awareness of COVID-19 was growing, and the effect of lockdown. Nearly 50% of the decrease in activity after February can be attributed to reduced activity in March, and the remaining to the lockdown.

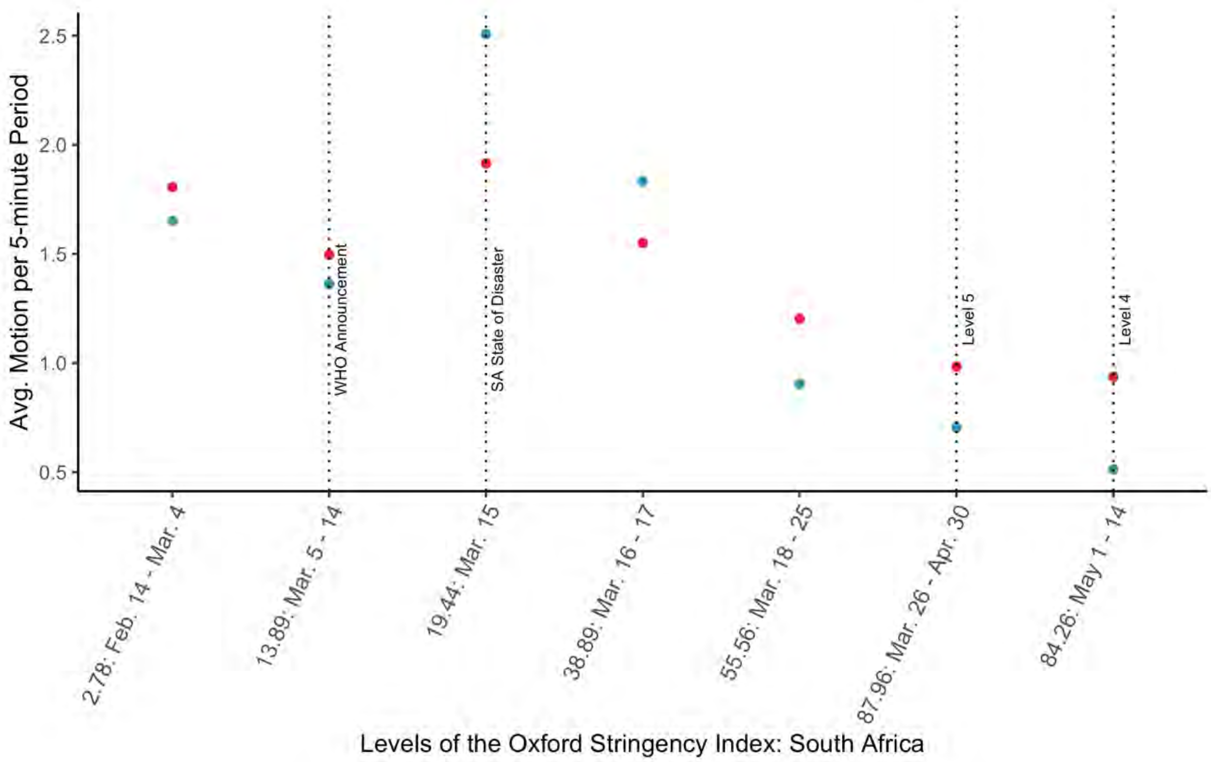
In compounds, the decrease in nighttime compound activity under lockdown is larger. Comparing the five-minute mean during lockdown to February 2020, there is a 61% decrease in motion. Compared to the entire pre-lockdown period, the lockdown is associated with a 57% decrease in nighttime triggers during lockdown ($p < 0.01$), with an average of 0.63 triggers per five-minute period, which is about 7.56 triggers per hour, down from about 17.65 triggers per hour, on average, before lockdown (Appendix B Table 2, column 9). Again, using the results from Appendix B Table 1 (column 2), we see a 19% reduction in activity between February (weeks 1 – 3) and the three weeks before lockdown (4 – 6), which captures about 32% of the overall decrease in nighttime activity after February — thus, COVID-19 awareness appears to have a smaller effect in these small, semi-private spaces compared to paths.

If we change the lockdown date to March 11 (the WHO pandemic announcement) or March 15 (South Africa state of disaster announcement) the results change very little (results available from the authors upon request). We also re-run the analysis controlling for each lockdown level (Levels 5, 4, and 3) separately using both the larger data set with 60 path and 26 compound sensors (but only up to May 14, 2020) and the smaller data set with 21 path and 18 compound sensors (up to June 18, 2020) and find that Level 5 and Level 4 show very similar activity patterns. Only in Level 3 do activity patterns resume on paths, but not in compounds (Appendix B Table 2, columns 5-8 and 13-16).

4.2 IMPACT OF GOVERNMENT REGULATIONS ON ACTIVITY

The previous analysis suggests that the implementation of lockdown restrictions in South Africa and any coincident increase in awareness of COVID-19 was fuzzy. To check this hypothesis, we use Oxford University's Coronavirus Government Response Stringency Index (SI) for South Africa, which also tracks government COVID-19 measures by day for many other countries. The index value does not necessarily change daily, so we replace the lockdown dummy with the SI index coded as a categorical variable. We see that activity is not simply decreasing in lockstep with increasing levels of stringency. Figure 3 (columns 2 and 4 in Appendix B Table 3) shows how mean motion changes with each of the seven SI levels during the study period. All changes are significant at the 99% level and are calculated with respect to the first level (2.78). For both paths and compounds, the level 19.44 (mid-March, week 5), the day a state of disaster is announced, is associated with a significant increase in nighttime motion, but it is only one day. For compounds only, level 38.89 (also week 5) is also associated with a significant increase in activity. Figure 3 reflects the results discussed above: the largest decrease in motion actually seems to occur between levels 38.89 and 55.56 (weeks 5 and 6), the week the state of disaster is announced and the week the lockdown is announced, but the lowest average motion is still during the lockdown (87.96 in Level 5 and 84.26 in Level 4).

Figure 3. Average 5-minute motion by levels of the Oxford Stringency Index for South Africa



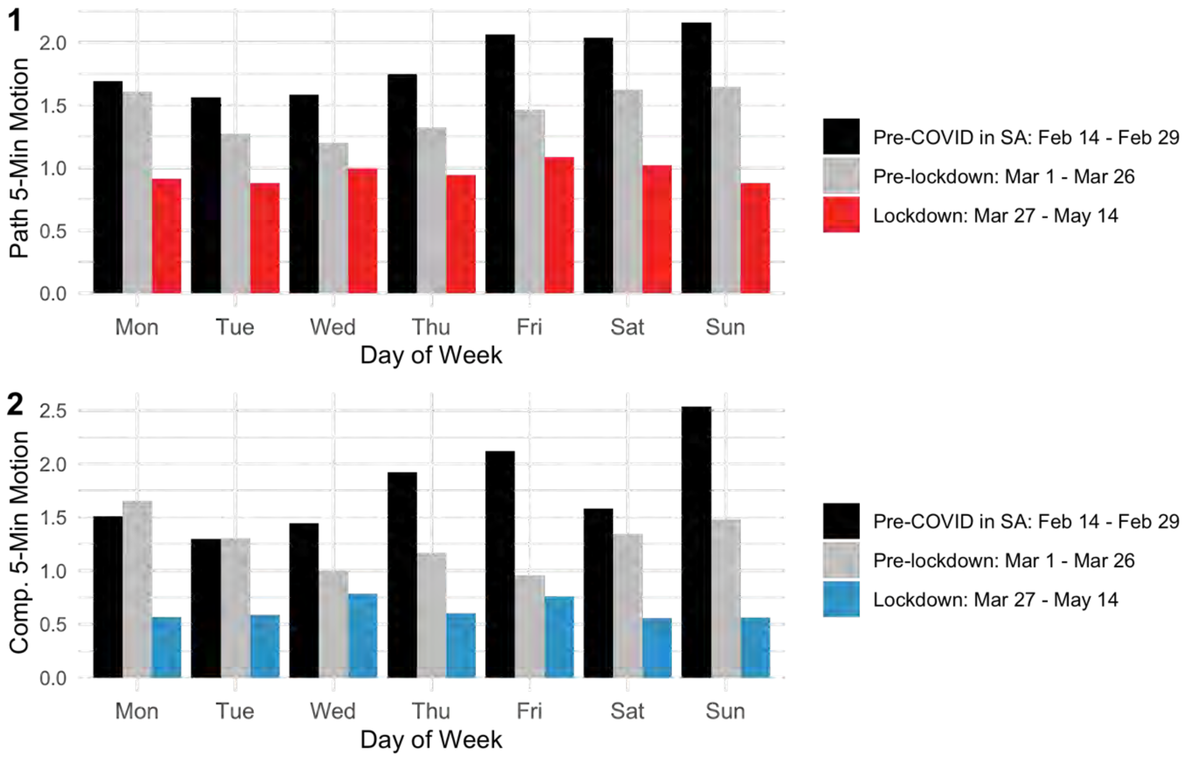
Red dots represent path averages and blue dots represent compound averages.

4.3 IMPACT OF LOCKDOWN ON DAILY AND HOURLY MOBILITY

To analyze what is driving the significant drop in average nighttime activity in both paths and compounds, we study the effect of the lockdown on particular days of the week and hours of a day (see equation 1 and Appendix B Tables 4 and 5).

In both paths and compounds, the largest decreases in average five-minute motion are seen on Saturday and Sunday nights (a decrease of 44% and 52% in paths, respectively, and 62% and 69% in compounds, respectively; Appendix B Table 4). Prior to the lockdown, the average week follows a cycle with higher nighttime activity during the weekends. During the lockdown the cyclical pattern disappears and all of the nights look remarkably similar (Figure 4), indicating that residents were mostly restraining outdoor social activities (on the weekend) and, to some extent, non-essential travel during the week. If we interact each lockdown stage with each day of the week, we see little difference between Level 4 and Level 5 in both paths and compounds (results available from the authors upon request).

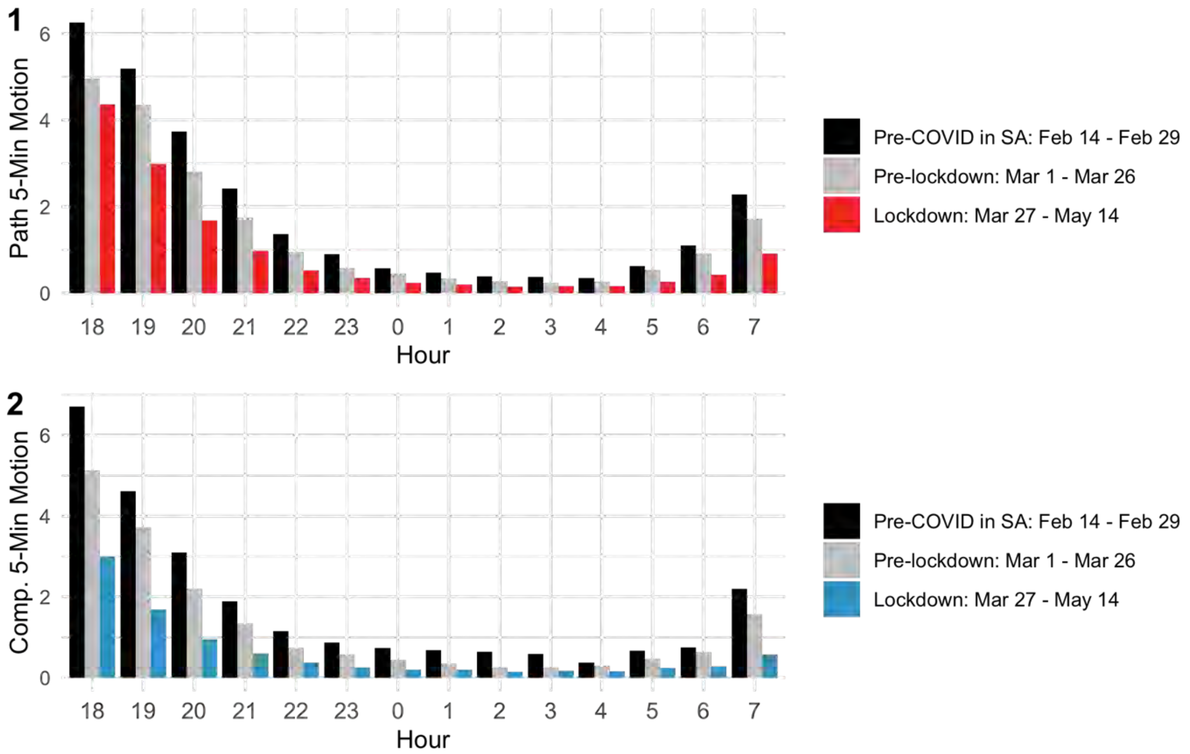
Figure 4. Average five-minute motion by day of week



The graphs show the five-minute average by day of week for the month of February, the month of March before lockdown, and for the lockdown period. Table of results with February included separately available from the authors upon request.

In a next step, we study the hours that drive activity declines. In paths (Figure 5, Panel 1, Appendix B Table 5, columns 1 and 2), there is a significant decrease in activity during lockdown for every hour ($p < 0.01$ for all hours except hour 5; hour 5 is $p < 0.1$). The largest decreases (in absolute terms) are between 6:00 – 9:00 pm, and from 6:00 – 8:00 am. The results indicate that people are curtailing activity around the primary commuting and social times, but the reduction, especially between 6:00 – 9:00 pm, is not as large as expected given that it was against the law to be outside for non-essential reasons under the lockdown during these times.

Figure 5. Average five-minute motion by hour



The panels show the average five-minute motion by hour in the dataset for the month of February, the month of March before lockdown, and for the lockdown period for paths (1) and compounds (2), respectively. Table of results with February included separately available from the authors upon request.

In compounds (Figure 5, Panel 2), the largest decreases (in absolute terms) are also between 6:00 – 9:00 pm, as well as from 7:00 – 8:00 am (Appendix B Table 5, columns 3 and 4). In both paths and compounds, the small absolute differences between means before and during lockdown in the middle of the night might indicate that motion then can be attributed to activities that residents cannot avoid, e.g., going to the toilet, etc., unlike social activities, which can be avoided in the evening hours.

One key difference between Level 5 and Level 4 of the lockdown is that South Africans were allowed to be outdoors for recreational (non-essential) activity between 6:00 and 9:00 am beginning May 1, 2020. Despite this rule relaxation, when we interact lockdown level with hours of the day, we do not see a significant increase in path activity between 6:00 – 8:00 am from Level 5 to Level 4 (results are available from the authors upon request). These results suggest that although there were slight changes to the rules between Level 5 and Level 4, residents did not radically change their nighttime behavior, at least not in early May.

5. DISCUSSION

Despite concerns about lockdown compliance in informal settlements, we find significant reductions in activity between 6:00 pm and 8:00 am on pedestrian paths (down by about 48%) and in shared, semi-private spaces called compounds (down by about 61%) compared to activity in February 2020. Importantly, activity already started to decline three weeks before the lockdown, particularly in paths (already 23% in March), when COVID-19 was quickly spreading worldwide and South Africa declared a state of emergency. The results are similar when we use the Oxford Stringency Index as the explanatory variable.

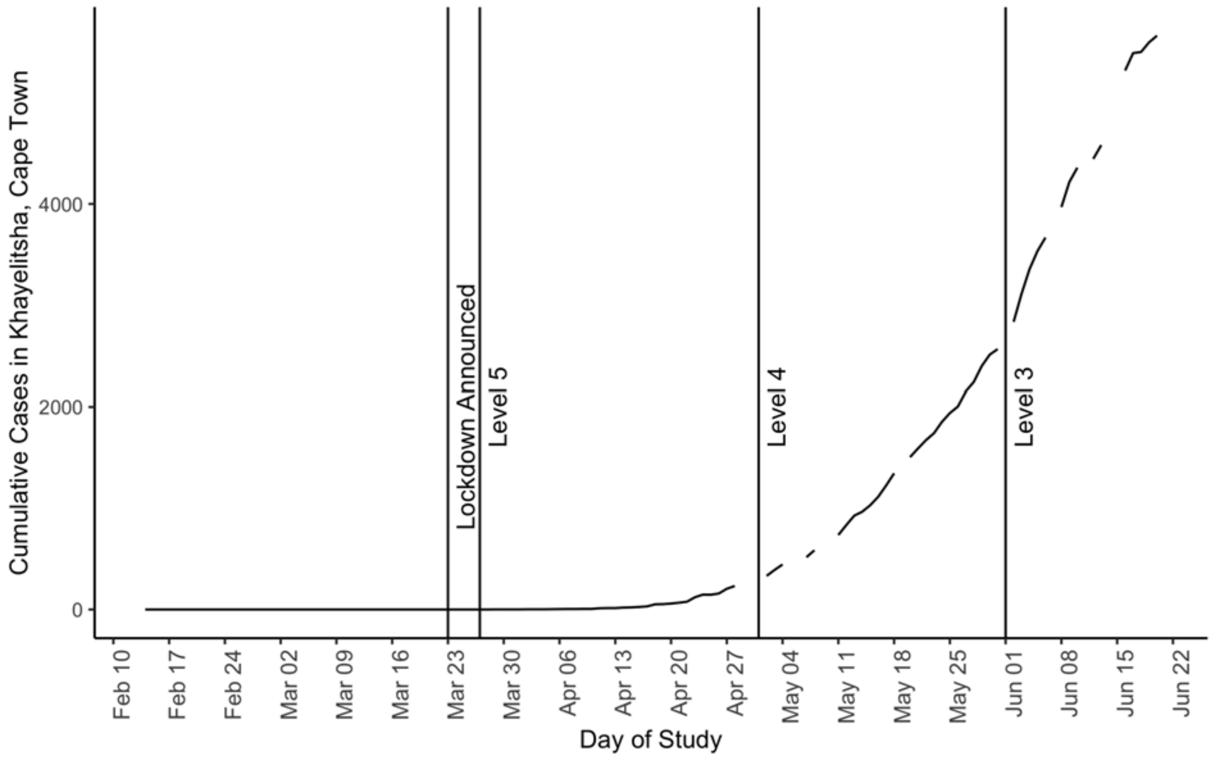
However, motion in the evening, nights, and early mornings never disappeared during lockdown, even when it was against the government rules. Our results further show that after the lockdown each day began to look similar with regard to motion, rather than following the usual ebb and flow of a typical week, which tends to have higher weekend activity in residential areas. In other words, activity decreased the most during weekends. Moreover, we find that in evenings and mornings — typical commute hours — activity decreased more than during the late evenings and nights. Although we see the largest reduction during commute hours, we still see more activity in those hours, on average, than in the middle of the night.

Taken together, the reduction in nighttime activity in this informal settlement indicates more compliance with the lockdown regulations than was portrayed in many media reports, but also that people reduced activity in response to growing awareness of COVID-19 before lockdown. This finding is consistent with other studies (Cronin & Evans, 2020; Lee et al., 2020), in particular a study in the US by Cronin and Evans (2020), who find dramatic mobility declines between March 8 – 14, 2020 prior to the onset of most lockdowns, but when many areas had announced a state of emergency. They find that state of emergency declarations account for 7-28% of the declines they measure. When we compare week-to-week five-minute motion means in March to February, we see that the decline for paths is on par with their results (23%). For compounds, however, the week-to-week change in March is inconsistent, but overall, there is still a 19% decrease compared to the three first three weeks of the study. This difference between paths and compounds suggests that behavior linked to transit, rather than say, socializing outdoors, may have been just as influenced by growing media attention to COVID-19 as the lockdown, while the lockdown may have been more influential in driving activity reductions in compounds.

Moreover, in the first week of lockdown the five-minute mean (1.15) is not as low as in subsequent weeks. One explanation is that residents had not realized how strict the implementation would be or how serious the threat was and therefore, had not yet dramatically adjusted their behavior. When we showed the results to our local field workers, they had two explanations. First, the first day of lockdown was the last Friday of the month, when many workers receive wages. In the absence of COVID-19, they would expect March 27 to have more nighttime activity than the previous weeks because most people would have just received a paycheck. Payday, in concert with pressure to prepare for lockdown, may have motivated a flurry of activity. Second, they said that while many people were fearful of the virus, others did not take lockdown regulations seriously until they saw on TV that other countries also had lockdowns and until the police and army began enforcing restrictions. Durizzo et al.'s (2020) results echo this speculation — they find that the South Africans in their sample are more likely to perceive the government's actions against COVID-19 as too extreme and tend to underestimate the number of cases in the country. In addition, in comparison to Ghanaians, South African respondents tend to the extremes — either they followed most or none of the rules. They also find that more than 80% report informing themselves about the pandemic by watching TV.

Furthermore, the first COVID-19 case in Khayelitsha was not documented until March 29, 2020, supporting the point that the risk may not have been salient right away. Figure 6 shows the COVID-19 case trajectory in Khayelitsha from February 14 – June 20, 2020. Indeed, there were few reported cases until Level 4 lockdown began in May 2020. Field team members said they knew of only one person from the neighborhood who had tested positive for COVID-19 as of October 2020. Unfortunately, due to data limitations we cannot say anything about how the changes in nighttime activity we observe relate to the spread of COVID-19, however, the case data contextualize what was going on in the vicinity of the informal settlement then.

Figure 6. Cumulative reported cases of COVID-19 in Khayelitsha, Cape Town



These data were collected by the authors from press releases put out by the Western Cape Premier Alan Winde. Gaps in the line indicate days in which no press release with Khayelitsha-specific data was publicly available.

Activity declines in paths of 48% and in compounds of 61% (compared to February), while generally lower than those found in higher-income countries (Intervista, 2020; Molloy et al., 2020), are consistent with findings based on Google Mobility data in several African countries (Bargain & Aminjonov, 2020) and a study using phone location data in Mumbai (Sheng et al., 2021). In comparison, two Swiss mobility studies find activity drops more sharply at the start of the lockdown (though they decline somewhat beforehand), but mobility levels climb more quickly afterwards (Intervista, 2020; Molloy et al., 2020). Though, notably, the lockdown in South Africa was much stricter than in Switzerland. One reason we might observe such a substantial drop in activity is that residents did not socialize outside after dark. Another reason could be that if residents commute less other activities that might occur at night, such as doing evening chores and procuring food, may instead happen during the day.

While we do not know which activities drive our results, the day-of-week and hour-of-day analyses provide ideas. The day-of-week analysis shows large declines in weekend activity (Appendix B Table 4). Our local field team said they observed fewer people out on weekends, but some may have just socialized indoors. The hour-of-day analysis shows that activity does not disappear, even at specific times when it is not allowed (e.g., after 8:00 pm during Level 4). Our team suggested that declines in the evening were not as large as the morning (Appendix B Table 4) because there were always some people out, though fewer than normal. From around midnight to 4:00 am, the field workers attribute the decrease in activity to fewer criminals out in paths. This interpretation tracks with reports that crime was markedly down early in the lockdown (BBC, 2020; Delbridge & Waseem, 2020).

Strangely, we notice that although people were allowed to be out for recreational activities between 6:00 am and 9:00 am under Level 4 restrictions, we observe a decrease in activity between 6:00 am and 8:00 am. Our local field staff said people may not have taken advantage of the rule relaxation because it was dark until around 7:20 am (sunrise) and that those who did exercise left the informal settlement, so they likely produced few additional triggers. Notably, June in the southern hemisphere is analogous to December in the north, meaning these are some of the longest nights of the year in Cape Town.

Larger activity reductions on weekends and in compounds (in comparison to paths) suggest that the nighttime activity that persisted after lockdown was mainly driven by pedestrian activity, rather than more stationary activities like socializing, which may explain the large decline in compound activity once the lockdown was in place, but not before. The time patterns we observe indicate that, even when it is against regulations, residents may go out to secure basic necessities, use sanitation infrastructure, socialize despite restrictions, or pursue economic opportunities even if they risk COVID-19 exposure.

6. ROBUSTNESS CHECKS AND LIMITATIONS

Part of the effect we document could be explained by seasonality and/or temperature. March is the end of summer/early fall in Cape Town, so days are getting shorter and cooler throughout the study. On Feb. 14, 2020, sunrise occurred at 6:19 am and sunset at 7:40 pm, while on May 14 sunrise was only at 7:31 am and sunset as early as 5:53 pm[18], so the daytime was about three hours shorter. To see if seasonality drives our results, we drop observations between 6:00 and 7:00 pm and between 7:00 and 8:00 am, since these hours were sometimes, but not always dark during our study period, and then re-run the main analysis. We find a 45.8% decrease in paths and a 59.9% decrease in compounds, a similar effect as in our main results, suggesting seasonality is not a main driver (Appendix B Table 6).

Moreover, using the full range of hours as well as hourly weather data for Khayelitsha from OpenWeather (OpenWeather, 2021), we re-run the main analysis controlling for hourly temperature, as well as time effects (hour of day and day of week dummies). In paths, we find lockdown is associated with 6.6 fewer triggers per hour (about 0.5 per five-minute period), which is a smaller decrease than in our main result (7.7 per hour or 0.64 triggers per five-minute period), but significant at the 99% level. In compounds, lockdown is associated with 9.6 fewer triggers

[18] Sunrise and sunset times are available here: https://www.timeanddate.com

per hour (about 0.8 per five-minute period), which is just a slightly smaller decrease (also significant at the 99% level) than in the main results (10 per hour or 0.84 triggers per five-minute period) (Appendix B Table 6). We conclude that temperature does have some mitigating effect on the relationship between lockdown and nighttime activity, as expected, however, this effect does not substantially alter the conclusion based on our main results.

Although our main results appear to be robust, there are several limitations that should be considered when assessing these findings. First, since we do not collect accurate data for all 24 hours of the day, we cannot study how daytime activity changed in response to lockdown and whether nighttime activity is displaced to daytime hours (which can be seen in Google Mobility data for the Western Cape in Appendix B Figure 3). While this limitation is not a substantial problem in the analysis for which the sensors were intended, it leaves us with a gap in understanding the response to lockdown in informal settlements. Second, due to sensor attrition we do not have as much data for all of Level 4 (May 2020). Still, as our analysis using the smaller dataset shows, this limitation may not have a major impact on our main result. In addition to study duration, sensor attrition also limits the overall sample size in an already somewhat small informal settlement. Out of 121 path sensors and 50 compound sensors originally installed, only about half have complete data in the relevant time period. Even though we do not believe there is systematic bias in attrition, we cannot rule it out.

The third limitation has to do with the nature of the sensor data. Since we know nothing about the passersby, it is difficult to be certain if the count represents several unique individuals or one person repeatedly triggering the sensor. This uncertainty is particularly problematic in compounds. Since compounds do not allow through traffic and frequently have a gate that is locked at night, any activity detected by the sensors is probably from the residents sharing the compound, rather than someone in transit. Just one person in a compound can create many triggers just by moving a lot within the space, therefore, less activity by even one person could potentially create an outsized effect on the trigger counts recorded by the sensor.

Although mobile phone data does not suffer from this limitation or limits on daytime measurement, they have other shortcomings: in informal settlements mobile phones are often shared (Sheng et al., 2021), in our context pre-paid cellular data is expensive and not always affordable, and mobility tracking apps are limited by GPS accuracy, making it hard to identify tracks. Furthermore, in our setting we learned from an earlier survey that only 38% of respondents report carrying a mobile phone outside with them at night for fear of theft. Thus, using mobile phone data would likely have created larger measurement errors.

7. CONCLUSION

Despite both widespread concerns about lockdowns in informal settlements and highly publicized skepticism about whether residents in these neighborhoods adhere to them, we find quantitative evidence that residents in one informal settlement in Cape Town, South Africa significantly limit nighttime mobility in response to state-mandated lockdowns of public life, but also in response to media coverage of and government communication about the pandemic prior to the lockdown. Using nighttime motion sensor data from a pre-existing project, we show activity in both paths and compounds began declining throughout March by 23% in paths and 19% in semi-private shared spaces, called compounds (in comparison to February) when COVID-19 cases were on the rise in Europe and the US, but that the lockdown itself had a substantial additional and sustained effect. Evening, nighttime, and early morning motion in paths went down by 48%, in comparison to February. In compounds, activity decreased by nearly 61% in comparison to February. Breaking this result down by day of week and hour of day, we find the largest decreases in nighttime activity on Saturday and Sunday and during commute hours between 6:00 – 9:00 pm and 6:00 – 8:00 am. These findings are consistent with the regulations in place in South Africa at the time — that is, a ban on all non-essential social activity (including alcohol and cigarettes) and a sharp reduction in businesses allowed to operate, resulting in severe unemployment (HSRC, 2020).

The motion sensors we use to gather data for this analysis only record accurate date in the evening, night, and early morning and record no details about passersby, meaning the data are helpful for understanding the use of public space at night, but not for learning more about *who* is using it or *why*. In addition, although we use hyper-local data in an under-studied context (also as a result of lockdown regulations in place worldwide) and we cannot identify causal effects, our results are remarkably similar in direction and magnitude to mobility studies of developing countries using much larger datasets, like Google Mobility data (Bargain & Aminjonov, 2020; Bharati & Fakir, 2020; Google LLC, n.d.; Sheng et al., 2021; Yilmazkuday, 2020).

Accounting for competing factors, such as weather and daytime seasonality, does not change our results much. Therefore, changes in behavior due to less daylight do not seem to drive the results. When we control for temperature, the activity reduction in both paths and compounds is somewhat smaller, but still significant. Therefore, it seems plausible that people were not just following the law or staying inside more due to bad weather, but also reducing activity because a) they were aware the virus is dangerous and b) there may have already been less work or fewer social events prior to the official lockdown since recommendations to social distance and school closures began nearly two weeks prior.

While we may demonstrate descriptive evidence that compliance with social distancing measures is possible in informal settlements to some extent, that does not necessarily mean that broad lockdowns are the most effective strategy in these neighborhoods. Although evening and early morning activity in both paths and compounds was significantly lower, it never entirely disappeared, suggesting that either a) people were trying their best to constrain their time in public, but certain activities were either essential, too important for other reasons to give up, or not considered to be dangerous or b) residents had displaced as much outdoor activity to daylight hours as possible (which we cannot accurately measure) and what we measure is a level of nighttime activity that is unavoidable in an informal settlement. Furthermore, activity was already declining in paths prior to the lockdown, suggesting that information and less strict measures also had an influence.

Still, it is notable that activity reaches a low point shortly after the start of lockdown and stays low through the end of the main study period, in contrast to the Swiss examples using phone tracking apps (Intervista, 2020; Molloy et al., 2020) where residents increase mobility again shortly after lockdowns are put in place. While the Swiss lockdown was far less stringent than in South Africa (see Appendix B Figure 4), the comparison illustrates why sensationalized media reports that residents of informal settlements did not follow lockdown rules are likely misrepresentations.

Without knowing the precise mechanism motivating residents' choices about when and how much to adhere to lockdown regulations, it is still possible to draw lessons for policy. The fact that activity during nighttime hours, especially commute hours, decreased, but still represented the highest level of activity throughout the measured hours indicates that lockdown regulations reduce outdoor activity, but that future efforts to manage contagious diseases must focus on the activities taking place during these time periods. First, mitigating the need for people to leave their homes to access sanitation or water could lead to further reductions in activity and reduce the number of contact points with neighbors. Second, pandemic response should not ignore the sheer density of informal settlements and the fact that households tend to be multigenerational and fluid. Since homes are small, many otherwise private activities take place in shared or semi-private spaces, such as washing or hanging laundry. Third, addressing the fact that most residents of informal settlements cannot sustain long periods without work and often need to work outside the home is essential. It is impossible to ask people to forego the basic activities of daily life, therefore, policymakers cannot implement a single lockdown policy that does not acknowledge the unique characteristics of life in informal settlements.

8. APPENDIX B

Figure 1. Pedestrian motion sensor

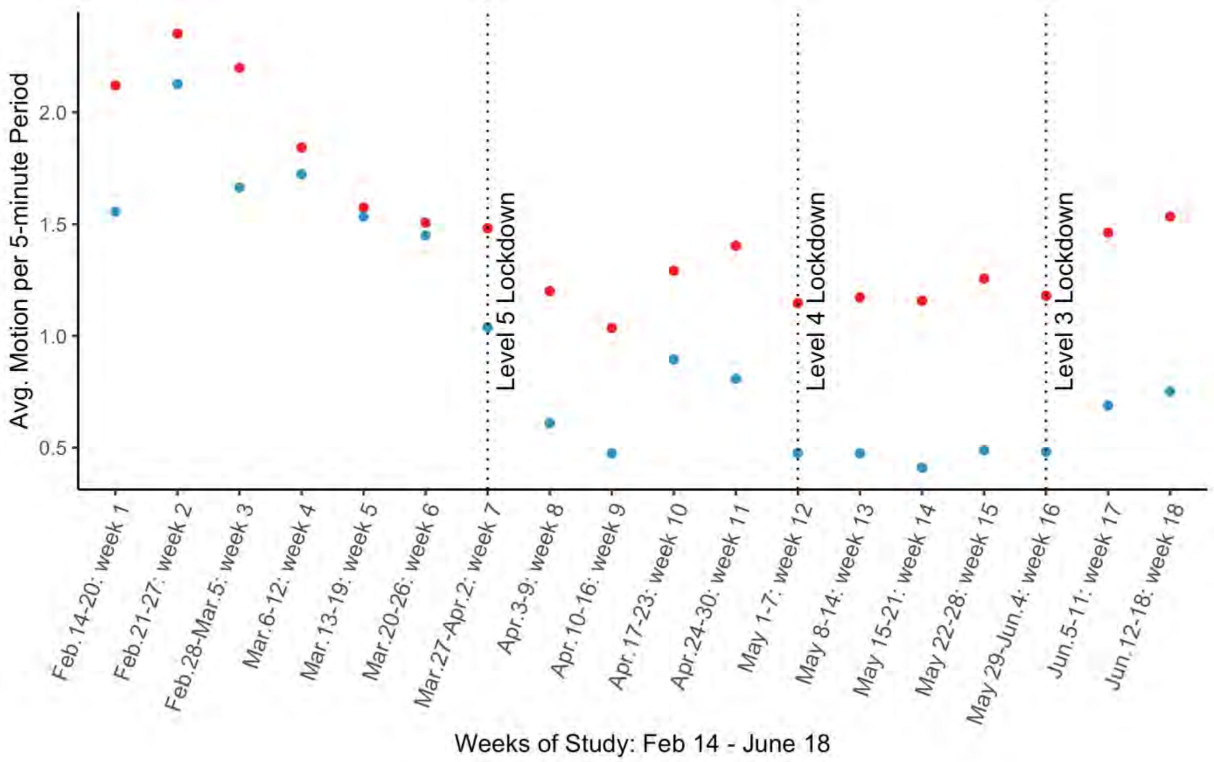
A pedestrian motion sensor installed in an informal settlement in Cape Town, South Africa.

Table 1. Changes in average five-minute motion by week of the study

	Feb 14-May 14 Data		Feb 14-Jun 18 Data	
	Paths	Compounds	Paths	Compounds
	(1)	(2)	(3)	(4)
Week 1: Feb.14-20 (constant)	1.698***	1.340***	2.121***	1.555***
	(0.012)	(0.020)	(0.025)	(0.126)
Week 2: Feb.21-27	0.137***	0.627***	0.232***	0.571***
	(0.017)	(0.032)	(0.037)	(0.188)
Week 3: Feb.28-Mar.5	0.139***	0.242***	0.079**	0.109
	(0.017)	(0.029)	(0.034)	(0.130)
Week 4: Mar.6-12 (WHO Announcement)	-0.176***	0.108***	-0.278***	0.168
	(0.016)	(0.029)	(0.032)	(0.254)
Week 5: Mar.13-19 (State of Disaster)	-0.256***	0.154***	-0.546***	-0.022
	(0.016)	(0.029)	(0.033)	(0.129)
Week 6: Mar.20-26 (Lockdown Announced)	-0.427***	-0.343***	-0.613***	-0.106
	(0.015)	(0.025)	(0.030)	(0.275)
Week 7: Mar.27-Apr.2 (Level 5 Begins)	-0.550***	-0.286***	-0.639***	-0.518***
	(0.015)	(0.026)	(0.032)	(0.128)
Week 8: Apr.3-9	-0.781***	-0.784***	-0.921***	-0.946***
	(0.014)	(0.022)	(0.030)	(0.135)
Week 9: Apr.10-16	-0.854***	-0.845***	-1.086***	-1.081***
	(0.014)	(0.022)	(0.029)	(0.126)
Week 10: Apr.17-23	-0.757***	-0.715***	-0.829***	-0.661**
	(0.014)	(0.023)	(0.031)	(0.267)
Week 11: Apr.24-30	-0.707***	-0.688***	-0.717***	-0.748***
	(0.014)	(0.023)	(0.032)	(0.217)
Week 12: May 1-7 (L4 Begins)	-0.746***	-0.837***	-0.974***	-1.080***
	(0.014)	(0.022)	(0.029)	(0.126)
Week 13: May 8-14	-0.777***	-0.817***	-0.948***	-1.081***
	(0.014)	(0.022)	(0.029)	(0.126)
Week 14: May 15-21			-0.963***	-1.146***
			(0.030)	(0.126)
Week 15: May 22-28			-0.864***	-1.067***
			(0.031)	(0.126)
Week 16: May 29-Jun.4 (L3 Begins)			-0.941***	-1.074***
			(0.029)	(0.126)
Week 17: Jun.5-11			-0.659***	-0.867***
			(0.032)	(0.127)
Week 18: Jun.12-18			-0.587***	-0.804***
			(0.033)	(0.127)
Observations (K)	1,074.445	472.000	476.102	436.683
Adjusted R2	0.017	0.023	0.014	0.001

Note: Left out group is week 1 in each data set (Feb 14 – Feb 20, 2020). The results in columns 1 and 2 include data from 60 path sensors and 26 compound sensors; the results in columns 3 and 4 include data from 21 path sensors and 18 compound sensors. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p <0.01

Figure 2. Average five-minute motion by week.



The plot shows mean five-minute motion for every week of the extended study until June 18, 2020 with the reduced sample of sensors. Red points represent path means; blue points represent compound means. See Appendix B Table 1 for regression results.

Table 2. Effect of South Africa's lockdown on nighttime activity

	Paths				Paths (Inc. June)				Compounds				Compounds (Inc. June)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(16)	(4)
Week 1: Feb.14-20 (constant)	-0.643***	-0.658***			-0.668***	-0.714***			-0.841***	-0.844***			-1.045***	-1.101***		
	(0.005)	(0.005)			(0.011)	(0.010)			(0.010)	(0.009)			(0.067)	(0.074)		
Week 2: Feb.21-27			-0.633***	-0.650***			-0.662***	-0.706***			-0.795***	-0.796***			-0.910***	-0.872***
			(0.006)	(0.005)			(0.012)	(0.012)			(0.010)	(0.010)			(0.086)	(0.085)
Week 3: Feb.28-Mar.5			-0.665***	-0.678***			-0.774***	-0.818***			-0.959***	-0.965***			-1.215***	-1.341***
			(0.007)	(0.007)			(0.012)	(0.012)			(0.011)	(0.011)			(0.063)	(0.085)
Week 4: Mar.6-12 (WHO Announcement)							-0.497***	-0.551***							-1.000***	-1.117***
							(0.015)	(0.014)							(0.064)	(0.086)
Week 5: Mar.13-19 (State of Disaster)	1.602***	3.284***	1.602***	3.284***	1.944***	3.216***	1.944***	3.215***	1.471***	1.161***	1.471***	1.162***	1.674***	1.355***	1.674***	1.353***
	(0.005)	(0.033)	(0.005)	(0.033)	(0.009)	(0.028)	(0.009)	(0.028)	(0.009)	(0.022)	(0.009)	(0.022)	(0.063)	(0.051)	(0.063)	(0.051)
Sensor FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	1.254	1.254	1.254	1.254	1.490	1.490	1.490	1.490	1.020	1.020	1.020	1.020	0.980	0.980	0.980	0.980
L5 v. L4			-0.03***								-0.16***					
			(0.006)								(0.009)					
L4 v. L3							-0.28***								-0.22***	
							(0.014)								(0.011)	
Observations (K)	1,074.445	1,074.445	1,074.445	1,074.445	476.102	476.102	476.102	476.102	472.000	472.000	472.000	472.000	436.683	436.683	436.683	436.683
Adjusted R2	0.014	0.098	0.014	0.098	0.010	0.105	0.010	0.105	0.017	0.096	0.017	0.096	0.001	0.002	0.001	0.002

Note: Left out group is "level 0" (pre-lockdown) in all specifications. Results in columns 1-4 and 9-12 include data until May 14, 2020 from 60 path sensors and 26 compound sensors, respectively. Results in columns 5-8 and 13-16 include data until June 18, 2020 from 21 path sensors and 18 compound sensors. Robust standard errors are in parentheses in the main table. Welch's Two-Sample t-test of difference in means between Level 5 and 4 and between Level 4 and 3 reported in bottom panel and the standard errors are in parentheses. *p<0.1; **p<0.05; ***p <0.01

Table 3. Results of OLS regression using the Oxford Stringency Index (SI) as the predictor

	Paths		Compounds	
	Paths	**Compounds**	**Paths**	**Compounds**
	(1)	(2)	(3)	(4)
SA Stringency Index (cont.)	-0.009***		-0.012***	
	(0.000)		(0.000)	
Level: 13.89		-0.310***		-0.290***
		(0.010)		(0.017)
Level: 19.44		0.108***		0.855***
		(0.026)		(0.045)
Level: 38.89		-0.256***		0.182***
		(0.019)		(0.033)
Level: 55.56		-0.603***		-0.747***
		(0.010)		(0.018)
Level: 84.26		-0.870***		-1.140***
		(0.009)		(0.015)
Level: 87.96		-0.823***		-0.946***
		(0.007)		(0.012)
Constant	1.777***	1.806***	1.675***	1.652***
	(0.005)	(0.006)	(0.008)	(0.010)
Mean	1.254	1.254	1.020	1.020
Observations (K)	1,074.445	1,074.445	472.000	472.000
Adjusted R2	0.016	0.017	0.018	0.021

Note: In models 2 and 4, the index is converted to a categorical variable to better understand how activity responds to changes in levels. Robust standard errors are in parentheses. Results that include sensor fixed effects can be provided by the authors upon request. *p<0.1; **p<0.05; ***p <0.01

Table 4. Effect of lockdown by day of week

	Paths		Compounds	
	(1)	(2)	(3)	(4)
Lockdown (=1)	-0.720***	-0.736***	-1.039***	-1.042***
	(0.015)	(0.014)	(0.026)	(0.024)
Tuesday	-0.265***	-0.266***	-0.306***	-0.306***
	(0.016)	(0.016)	(0.031)	(0.030)
Wednesday	-0.305***	-0.304***	-0.453***	-0.453***
	(0.016)	(0.015)	(0.031)	(0.029)
Thursday	-0.169***	-0.168***	-0.187***	-0.187***
	(0.017)	(0.016)	(0.032)	(0.030)
Friday	0.132***	0.132***	-0.065**	-0.065**
	(0.018)	(0.017)	(0.033)	(0.031)
Saturday	0.199***	0.200***	-0.143***	-0.143***
	(0.017)	(0.017)	(0.032)	(0.030)
Sunday	0.185***	0.187***	0.226***	0.226***
	(0.018)	(0.017)	(0.035)	(0.033)
Tuesday*Lockdown	0.232***	0.233***	0.326***	0.326***
	(0.020)	(0.019)	(0.035)	(0.033)
Wednesday*Lockdown	0.384***	0.383***	0.675***	0.674***
	(0.020)	(0.019)	(0.035)	(0.033)
Thursday*Lockdown	0.198***	0.197***	0.224***	0.222***
	(0.020)	(0.019)	(0.036)	(0.034)
Friday*Lockdown	0.039*	0.040*	0.258***	0.260***
	(0.021)	(0.020)	(0.037)	(0.035)
Saturday*Lockdown	-0.093***	-0.090***	0.133***	0.135***
	(0.021)	(0.020)	(0.035)	(0.034)
Sunday*Lockdown	-0.219***	-0.217***	-0.229***	-0.228***
	(0.021)	(0.020)	(0.039)	(0.036)
Constant	1.634***	3.315***	1.604***	1.294***
	(0.012)	(0.035)	(0.023)	(0.030)
Sensor FE	No	Yes	No	Yes
Mean	1.254	1.254	1.020	1.020
Observations (K)	1,074.445	1,074.445	472.000	472.000
Adjusted R2	0.017	0.101	0.019	0.098

Note: Left out group is Monday in all specifications. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 5. Effect of lockdown by hour of the day

	Paths				Compounds			
	(1)		(2)		(3)		(4)	
Lockdown (=1)	-1.097***	(0.034)	-1.112***	(0.031)	-2.722***	(0.067)	-2.724***	(0.064)
7 PM	-0.785***	(0.036)	-0.785***	(0.033)	-1.669***	(0.074)	-1.669***	(0.070)
8 PM	-2.293***	(0.033)	-2.293***	(0.031)	-3.193***	(0.068)	-3.193***	(0.064)
9 PM	-3.461***	(0.031)	-3.461***	(0.029)	-4.182***	(0.065)	-4.182***	(0.061)
10 PM	-4.350***	(0.031)	-4.350***	(0.029)	-4.831***	(0.063)	-4.831***	(0.060)
11 PM	-4.756***	(0.030)	-4.756***	(0.028)	-5.043***	(0.062)	-5.043***	(0.059)
12 AM	-4.964***	(0.030)	-4.965***	(0.028)	-5.178***	(0.062)	-5.177***	(0.059)
1 AM	-5.074***	(0.029)	-5.075***	(0.028)	-5.252***	(0.061)	-5.252***	(0.059)
2 AM	-5.142***	(0.029)	-5.143***	(0.027)	-5.334***	(0.061)	-5.334***	(0.058)
3 AM	-5.172***	(0.029)	-5.173***	(0.027)	-5.350***	(0.061)	-5.350***	(0.058)
4 AM	-5.162***	(0.029)	-5.162***	(0.027)	-5.414***	(0.060)	-5.414***	(0.057)
5 AM	-4.890***	(0.029)	-4.890***	(0.027)	-5.188***	(0.060)	-5.188***	(0.058)
6 AM	-4.473***	(0.029)	-4.473***	(0.027)	-5.060***	(0.060)	-5.060***	(0.058)
7 AM	-3.522***	(0.032)	-3.523***	(0.030)	-3.920***	(0.068)	-3.920***	(0.066)
7 PM * Lockdown	-0.590***	(0.043)	-0.590***	(0.040)	0.344***	(0.084)	0.344***	(0.080)
8 PM * Lockdown	-0.391***	(0.040)	-0.391***	(0.037)	1.130***	(0.078)	1.129***	(0.073)
9 PM * Lockdown	0.081**	(0.038)	0.081**	(0.035)	1.775***	(0.074)	1.774***	(0.070)
10 PM * Lockdown	0.515***	(0.037)	0.515***	(0.034)	2.192***	(0.073)	2.192***	(0.069)
11 PM * Lockdown	0.745***	(0.036)	0.745***	(0.034)	2.290***	(0.072)	2.289***	(0.068)
12 AM * Lockdown	0.839***	(0.036)	0.840***	(0.034)	2.370***	(0.071)	2.369***	(0.068)
1 AM * Lockdown	0.906***	(0.035)	0.907***	(0.033)	2.443***	(0.071)	2.443***	(0.068)
2 AM * Lockdown	0.930***	(0.035)	0.931***	(0.033)	2.470***	(0.070)	2.470***	(0.067)
3 AM * Lockdown	0.971***	(0.035)	0.972***	(0.033)	2.514***	(0.070)	2.513***	(0.067)
4 AM * Lockdown	0.962***	(0.035)	0.962***	(0.033)	2.563***	(0.069)	2.562***	(0.066)
5 AM * Lockdown	0.794***	(0.035)	0.794***	(0.033)	2.416***	(0.070)	2.416***	(0.067)
6 AM * Lockdown	0.533***	(0.036)	0.533***	(0.033)	2.333***	(0.070)	2.334***	(0.067)
7 AM * Lockdown	0.070*	(0.038)	0.070**	(0.036)	1.487***	(0.078)	1.487***	(0.075)
Constant	5.461***	(0.028)	7.144***	(0.037)	5.729***	(0.058)	5.420***	(0.059)
Sensor FE	No		Yes		No		Yes	
Mean	1.254		1.254		1.020		1.020	
Observations (K)	1,074.445		1,074.445		472.000		472.000	
Adjusted R2	0.286		0.370		0.159		0.237	

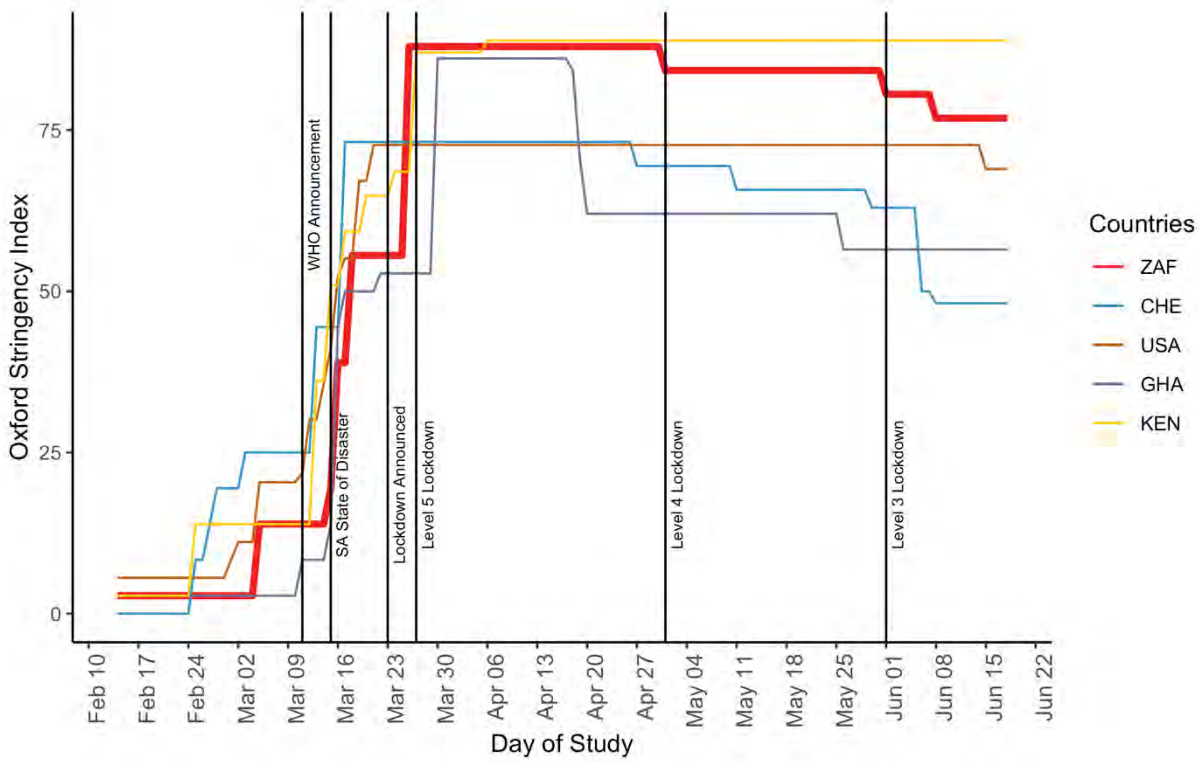
Note: Left-out group is "level 0" (before lockdown) and 0:00 (midnight). Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 6. Robustness checks

	Five-Minute Motion		Mean Hourly Motion	
	Paths (no 6PM / 7AM)	Compounds (no 6PM / 7AM)	Paths	Compounds
	(1)	(2)	(3)	(4)
Lockdown (=1)	-0.573***	-0.652***	-6.564***	-9.610***
	(0.005)	(0.009)	(0.283)	(0.657)
Temperature			0.825***	0.768***
			(0.063)	(0.139)
Constant	1.252***	1.088***	55.445***	50.625***
	(0.004)	(0.008)	(1.574)	(3.590)
Hour Dummies	No	No	Yes	Yes
Weekday Dummies	No	No	Yes	Yes
Mean	0.942	0.739	1.254	1.020
Observations (K)	920.924	404.572	75.578	32.981
Adjusted R2	0.016	0.015	0.401	0.181

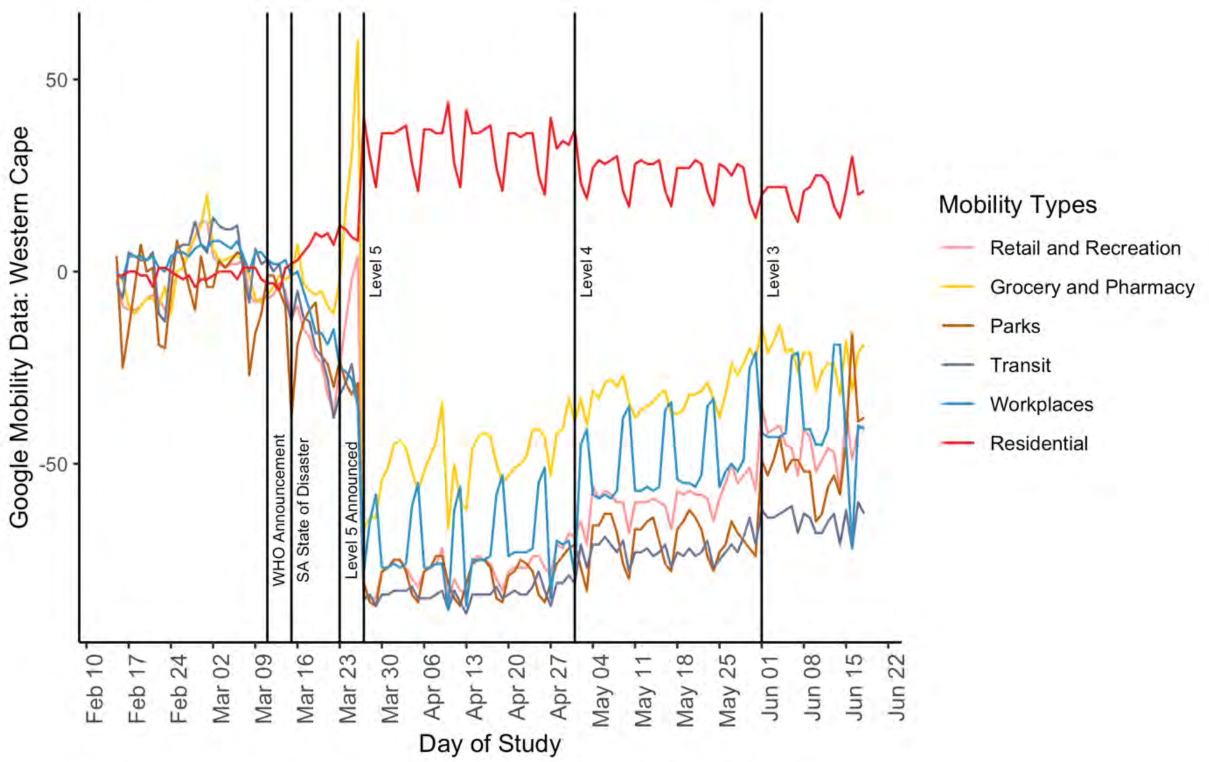
Note: We do not control for sensor fixed effects in these robustness checks, but the results including sensor fixed effects can be provided by the authors upon request. Robust standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01

Figure 3. Oxford Coronavirus Government Response Stringency Index for Five Countries



Using the Oxford Coronavirus Government Response Stringency Index, the figure shows the evolution of government responses to COVID-19 in South Africa (ZAF), Ghana (GHA), Kenya (KEN), the United States (USA), and Switzerland (CHE) over the course of the study period.

Figure 4. Google Mobility data for the Western Cape, South Africa from February 15 – May 14, 2020



Data downloaded from Google COVID-19 Community Mobility Reports. The Western Cape is the province which encompasses Khayelitsha and the City of Cape Town. Percent changes in activity are calculated with reference to Jan 3 – Feb 6, 2020.

ARTICLE 3: NOT ALL LIGHT IS RIGHT — A STUDY OF LIGHT LEVELS AND LIFE AT NIGHT IN A CAPE TOWN INFORMAL SETTLEMENT

Status: Working Paper

Authors: Yael Borofsky

1. INTRODUCTION

Public street lighting has gained renewed attention in the social sciences with the publication of the first large-scale randomized controlled trial showing that public lighting reduced crime in New York City housing projects both at night and during the day (Chalfin et al., 2021). This new evidence adds to a large literature that has found that public lighting can impact life at night in a wide variety of ways in addition to crime, from visibility to perception of safety, to nighttime activity. This literature, however, is almost entirely based on studies in formal urban areas, most often in high-income countries, with only a small number of qualitative studies looking at the role of light at night in informal settlements (Briers, 2021; Kretzer, 2021).[19]

Yet, urban environments vary substantially worldwide, as do types of public lighting. In particular, informal settlements —where more than 50% of the urban population in sub-Saharan Africa lives — are drastically different from formal urban areas (World Bank, 2021). These low-income neighborhoods typically have no formal planning, homes are often constructed out of temporary materials, and water and sanitation infrastructure is shared. Furthermore, many informal settlements lack sufficient or any access to street lighting and little data exist about how many informal settlements have access to public lighting. Auerbach (2020) reports that in the informal settlements he studies, there are 5.73 streetlights per thousand residents, on average, but it is unclear how that figure compares elsewhere in the world. Informal settlements represent a growing share of urban areas in many low- and middle-income countries, raising questions about how to provide public lighting in these neighborhoods and whether the same benefits of public lighting can be expected in different contexts.

Research from psychology suggests that neighborhood amenities, e.g., public infrastructure like public lighting, can have a positive impact on quality of life (Gandelman et al., 2012), indicating that access to quality lighting in informal settlements may not only be important for deterring crime, but also for enhancing other aspects of quality of life. Providing public light in informal settlements is not straightforward, however, as many are too dense for standard streetlighting

[19] Both of these dissertations were also written by doctoral students who were part of the ETH Zurich ISTP. Briers (2021) is a dissertation based on the same collaborative project as this study. For more details, see the Introduction of this dissertation.

and lighting standards rarely address these unplanned spaces. Among informal settlements that do have public lighting, high-mast lights, or 30-40-meter-tall flood lights, are one common technology found in sub-Saharan Africa, especially in South Africa (see Appendix C Figure 1). While high-mast lights have been the source of negative media attention in South Africa, due to protests for better lighting and vandalism (Damons, 2021; Mtembu, 2017; Ramphele, 2017), very few academic studies have evaluated the effectiveness of this type of lighting for informal settlements (Kretzer, 2020).

Furthermore, since the vast majority of research on public lighting is heavily focused in high-income cities, mainly in the US, Europe, and the UK, very little is known about how lighting in informal settlements influences the perception and experience of public space, despite the fact that residents need to enter public space to meet basic needs. So far, the research that exists on life at night in informal settlements, particularly as it relates to lighting, is largely qualitative (Briers, 2021; Kretzer, 2020; Kretzer & Walczak, 2020) or focused primarily on crime (e.g., Matzopoulos et al., 2020; Musoi et al., 2014). One reason for this knowledge gap may be the relative difficulty of doing research in these neighborhoods at night, given the lack of adequate public lighting and high crime rates.

To address these research gaps, I first use light (lux) measurements to assess the effectiveness of high-mast lighting in one informal settlement in Cape Town, by measuring brightness (illuminance) across the entire informal settlement and by conducting a case study to measure uniformity (even distribution of brightness) in one of the paths. Then, using data from a household survey conducted in March 2019 (N = 763) in the same neighborhood, I study the relationship between high-mast lighting and perceptions of safety, perceptions of crime risk, and reported nighttime activities. Based on the light measurements and the uniformity case study, I find that high-mast lighting is not evenly distributed throughout the entire neighborhood and that even in one wide path, uniformity of light is low. Using regression analysis, I only find an association between measured light levels and reported perception of safety at night on the brightest paths (10 lux or brighter). I also find that residents living in the brightest areas are more likely to forego certain measures intended to protect themselves in public space at night (e.g., leaving their mobile phone at home at night). Despite the fact that there is some relationship between light and perception of safety, I find that light levels have no influence on perceived risk of crime or on willingness to enter public space at night.

In assessing the efficacy of high-mast lighting and the way it shapes the experience of life at night in an informal settlement, this study makes two important contributions to the literature. First, to my knowledge, this is the first real-world analysis of how high-mast lighting performs in informal settlements, despite the fact that at least three countries use this technology for residential lighting in informal settlements. Therefore, the results have important policy implications for governments seeking solutions for public lighting in informal settlements.

Second, this is also the first study, to my knowledge, to quantitatively study the influence of high-mast lighting on three key aspects of the nighttime life: perception of safety, perception of risk of crime, and willingness to be in public space at night, providing new insight in the social sciences about the way public lighting shapes life at night in a different, but critically important urban context.

2. LITERATURE ON PUBLIC LIGHTING, PERCEPTION OF SAFETY, RISK OF CRIME, AND NIGHTTIME ACTIVITY

In this paper, I focus on three aspects of nighttime life: perceptions of safety, perceptions of crime risk, and willingness to enter public space at night. For the purposes of this study, perception of safety can be thought of as the emotional response to insecurity when it is dark out. This sense of insecurity could have many sources: limited visibility (Calvillo Cortés & Falcón Morales, 2016), inability to recognize other people (Wu & Kim 2018), previous victimization (Kaplan & Chalfin, 2021), and environment or neighborhood characteristics (Blöbaum & Hunecke, 2005; Nasar & Jones, 1997; Wu & Kim, 2018), to name a few. I follow the literature in considering perception of safety as a separate concept from perceived risk of experiencing a crime, which can be thought of as a cognitive risk assessment (how likely you think you are to experience a given type of crime), rather than an emotional response (Ferraro & LaGrange, 1987; Lorenc et al., 2014; Rountree & Land, 1996).[20] Willingness to engage in public space at night is defined here as the willingness to go outside after dark for any reason, be it social, economic, or other activities. Given that many studies evaluate the relationship between light and at least two of these outcomes, I review the literature all together.[21]

Many studies of the impact of public lighting on perception of safety point to a positive relationship, but not all (Struyf, 2020). For example, Painter (1996) finds that about 90% of pedestrians interviewed in three "potentially dangerous streets" in London reported feeling safer after a street lighting improvement. Fotios et al. (2015) find 92% of photo interview respondents stated that the presence/absence of public lighting contributed to whether they would feel reassured walking on a street at night. In another study of eight locations on a German university campus after dark, Blöbaum and Hunecke (2005) find lighting is significantly associated with higher perception of safety. Nair et al. (1997) also find that a relighting project is Glasgow was

[20] There is an unsettled academic debate about the concepts of perception of safety and risk of crime (referred to as the risk-fear paradox by Lorenc et al. (2014)). Hence I use the definition that informed our measurements of perception of safety. For an overview of the theoretical and measurement debate, see Lorenc et al. (2014).

[21] The existing literature suggests nighttime is linked to a wide variety of aspects of quality of life at night including: visibility (Boyce, 2019; S. Fotios & Cheal, 2009; S. Fotios & Uttley, 2018), facial recognition (S. Fotios, Yang, et al., 2015; Yang & Fotios, 2015), economic and social activity (Boyce, 2019), perception of safety (Blöbaum & Hunecke, 2005; Nasar & Jones, 1997; Painter, 1996; Peña-García et al., 2015; Svechkina et al., 2020; Wu & Kim, 2018), reassurance or confidence walking alone at night (Fotios et al., 2019, 2015a; Nasar and Bokharaei, 2017), nighttime walking behavior (S. Fotios, Unwin, et al., 2015; Steve Fotios & Castleton, 2016) and crime (Chalfin et al., 2021; Doleac & Sanders, 2015; Domínguez & Asahi, 2019; Farrington & Welsh, 2002; Kaplan, 2019; Welsh & Farrington, 2008).

associated with an increased number of respondents reporting they felt safe walking on the street even very late at night. Most recently, Kaplan and Chalfin (2021) use a survey experiment to study response to a brighter lighting scenario on a Chicago street, finding that respondents assigned to the brighter lighting treatment group were 21% less likely to report feeling unsafe. On the other hand, Atkins et al. (1991) find no effect of a re-lighting program in London on feelings of safety, even though the majority of respondents approved of the lights.

Perhaps because of the conceptual fuzziness about the difference between perceived safety and perceived risk of crime (Jackson, 2005; Rountree & Land, 1996), far fewer studies report findings on the relationship between light at night and risk of crime. According to a meta-review by Lorenc et al. (2014), the recommended approach to measure perception of crime risk is to ask respondents how they perceive the risk of being the victim of several different crimes. Using this approach, Nair et al. (1997) find that after a Glasgow light improvement project perception of risk of crime declines slightly, but remains high, even though reported perception of safety increased. Atkins et al. (1991) find that improved street lighting is associated with a decrease in perceived risk of rape among elderly women, but that all women perceived a higher risk of other crimes, such as car theft.

There is also only limited evidence that improved lighting leads to behavior change in terms of willingness to engage in public space at night. Painter (1996) finds a 34-101% increase in pedestrian usage of relit streets among males and 45-71% increase among females. Rather than street lighting, Uttley & Fotios (2017) use DST to show that the additional hour of light was associated with a 62% increase in pedestrians, on average, based on six years of observations of the hour before and after the clock change. On the other hand, Kaplan and Chalfin (2021) find that respondents who were exposed to the brighter lighting treatment condition were not any more likely to say that they expect to go out at night more frequently.

Importantly, other factors may attenuate the relationship between light and these three outcomes of interest. Personal characteristics, such as gender and age may influence perception of safety and willingness to be in public space at night. Women and older people, on average, have been found to be more likely to fear for their safety and avoid going out at night (Blöbaum & Hunecke 2005, Chalfin & Roman, 2008). Other researchers emphasize the importance of familiarity with one's surroundings. Chalfin & Roman (2008) used length of residence as a percentage of participant age as an indicator of familiarity with the neighborhoods in Washington DC they studied and found it was associated with decreases in fear of crime ($OR = 0.489$, $p < 0.05$). On the other hand, Deka (2018) finds no relationship between length of residence in a New Jersey neighborhood and fear of crime or walking duration. Finally, Kaplan & Chalfin (2021) find weak evidence that previous crime victimization can also play a role.

Finally, characteristics of the built environment may also be important. For example, Blöbaum & Hunecke (2005) find that in addition to lighting, low perception of entrapment (the sense that it is difficult to escape a space) and concealment (the ability for a potential offender hide) are both linked to perception of safety and that when entrapment is high, lighting becomes less important. In an online photo survey study at a Virginia college, Wu & Kim (2018) find the most preferred scenario was a photo showing an area with "an open view with a low level of concealment" and respondents also rate that photo the safest out of 24 scenes. Again, Deka et al. (2018) find the opposite. After aggregating a variety of built environment characteristics into a "pedestrian friendliness" score, they find no effect of this aggregated score on fear of crime or walking duration.

While many studies simply analyze how the absence/presence or low/bright light affects safety and movement, a few studies have sought to determine which minimum light conditions are necessary to realize important benefits (Fotios and Castleton, 2016). Some studies argue that the way in which light affects nighttime behavior is dependent on brightness (Boyce et al., 2000; Peña-García et al., 2015) and how uniformly the light is distributed (Haans & de Kort, 2012; Markvica et al., 2019; Nasar & Bokharaei, 2017b; Peña-García et al., 2015; Wu & Kim, 2018). There is also evidence that the relationship between light and many positive benefits, like feelings of safety or recognition of facial expressions, is best described by an asymptotic or plateau-escarpment relationship (Boyce et al., 2000; Fotios & Castleton, 2016; Svechkina et al., 2020) — in other words, diminishing marginal returns to lighting.

A few studies have sought to specify an optimal illuminance level (lux level) that maximizes perception of safety and other benefits with the goal of guiding lighting standards. For example, Painter (1996) argues that the lighting improvement intervention she studied resulted in an average illuminance of 10 lux and a minimum of 5 lux, the British standard at the time for high crime risk areas, which was sufficient to drive her positive findings on safety and pedestrian activity. In a review of the literature, Boyce (2019) finds that 2 lux is the minimum level to ensure safe movement and that below 10 lux small increases in lux levels are associated with big increases in perceived safety. Another review by Fotios & Castleton (2016) suggests horizontal illuminances between 3-5 lux are sufficient, but that more testing is necessary. Finally, Svechkina et al. (2020) find that respondents report high levels of feelings of safety at about 5-10 lux, before returns to brighter light begin to diminish.

Brightness, however, is not the only factor. Wu & Kim (2018) find that respondents rate photos with bright lighting and low lighting as similarly safe, as long as the lighting is uniform. They also find that people perceive the highest safety when they can recognize another person's face clearly, indicating that uniformity can facilitate visibility. They point out that frequent changes in light levels may, in fact, trigger a fear response due to visual discomfort. Fotios et al. (2019) support this finding, arguing that uniformity may be a better predictor of similarity between daytime and nighttime perceptions of safety, than average illuminance alone.

It is important to note here that the vast majority of these studies suffer from methodological weaknesses, which may explain why there is quite a bit of contradiction between studies. As Kaplan and Chalfin (2021) point out in their review of the literature, several frequently cited studies are either purely qualitative in nature with very small sample sizes (Boyce et al., 2000; Fotios, Yang, et al., 2015; Painter, 1996), do not have a plausible control group (e.g., Painter 1996, Atkins 1991) or derive estimates based on simulated, rather than real-life, scenarios (e.g., Kaplan and Chalfin, 2021). Perhaps that is why a 2014 meta-review only finds a link between street lighting interventions and reduced fear of crime in uncontrolled studies, but the relationship disappears when they only considered controlled studies (Lorenc et al., 2014). Furthermore, almost every study took place in the United Kingdom, Europe, or the United States. Still, the proliferation of studies seeking to understand the role of public lighting underscores the irony that many people take its benefits for granted assuming there is no need to study it. Yet, a clearer sense of how public lighting can improve quality of life for residents in affected communities, might lead to greater public investment (Kaplan & Chalfin, 2021; Struyf, 2020). Such evidence is especially important in informal settlements, where public budgets are likely to be limited and neighborhoods typically exist outside formal legal and policy frameworks.

The lack of comprehensive data on informal settlements and public lighting likely contributes to the absence of literature on the relationship between light and life at night. News reports tout the installation of solar streetlights in some Indian cities, but it is unclear how widespread public lighting in informal settlements is countrywide (Kulkarni, 2014; Venkat, 2016). In Bogotá, government provides public lights to informal settlements that have gone through a legalization process, but before that happens residents frequently build their own streetlights (Kretzer, 2021). A study of four informal settlements in Kenya finds that despite the presence of high-mast lights, only about 12% of residents report feeling "safe" or "very safe" in these neighborhoods. In addition, residents report two different high-mast light locations to be crime hotspots and fewer than 2% of respondents mentioned lighting as a means of crime protection (Musoi et al., 2014). A recent news article reported that in Namibia, some informal settlements near Windhoek are also lit with high-mast lights, but it is not clear what the impact has been (Ikela, 2020).

3. STUDY BACKGROUND

In South Africa, those informal settlements that have public lighting most frequently have high-mast lighting.[22] High-mast lights were originally used as public lighting in South African townships (residential areas) zoned for Black Africans under apartheid (O'Regan et al., 2014). Today, because extreme density and/or land ownership issues make it difficult to deploy conventional streetlights, the City of Cape Town still installs this infrastructure on the perimeter of informal settlements (Cape Argus, 2018), with the intention that the high-mast lights will cast sufficient

[22] A small number of informal settlements, usually located on City of Cape Town-owned land, have public lighting installed on electricity distribution poles instead of high-mast lights.

light into the neighborhood. The 30-40-meter-tall luminaires cast light in a roughly 100-meter radius (see Appendix C Figure 1). These lights, however, are designed for open areas, like parking lots or sports stadiums, and anecdotal reports from residents suggest they provide patchy lighting in dense spaces, creating shadows and blinding bright spots in narrow pathways. A recent study simulating a best-case high-mast lighting scenario, where the informal settlement was modeled as a grid (never the layout of a real informal settlement), found that high-mast lighting was not an adequate means of providing public lighting (Kretzer, 2020).

Amongst residents in informal settlements with high-mast lighting, perceptions are mixed. In the last few years, there have been protests demanding adequate public lighting in Cape Town and demand for increased public lighting budgets for townships, such as Khayelitsha, which continue to suffer from marginalization and poverty today (Mtembu, 2017; Sachane, 2017). On the other hand, discussions with City of Cape Town public lighting officials reveal that residents of areas with high-mast lighting are often reticent to allow them to be removed, perhaps for fear that they will not be replaced with anything better.

In South Africa, the national standards for public lighting do not have an illuminance guideline for paths in informal settlements. For a low-volume (vehicle) traffic residential street, the standard minimum average horizontal illuminance of 2 lux, however, many informal settlements are made up of extremely narrow paths that no car could pass through, meaning this standard is likely not relevant.[23] The closest equivalent in the standard are wholly pedestrian streets in the city center, where the minimum average horizontal illuminance is 10 lux, indicating that pedestrian-only paths require brighter lighting (Sustainable Energy Africa, 2012). For reference, the illuminance of a full moon on a clear night is approximately 0.3 lux (Kyba et al., 2017).[24] Without a standard, there is no official way to determine whether high-mast lights constitute access to public lighting.

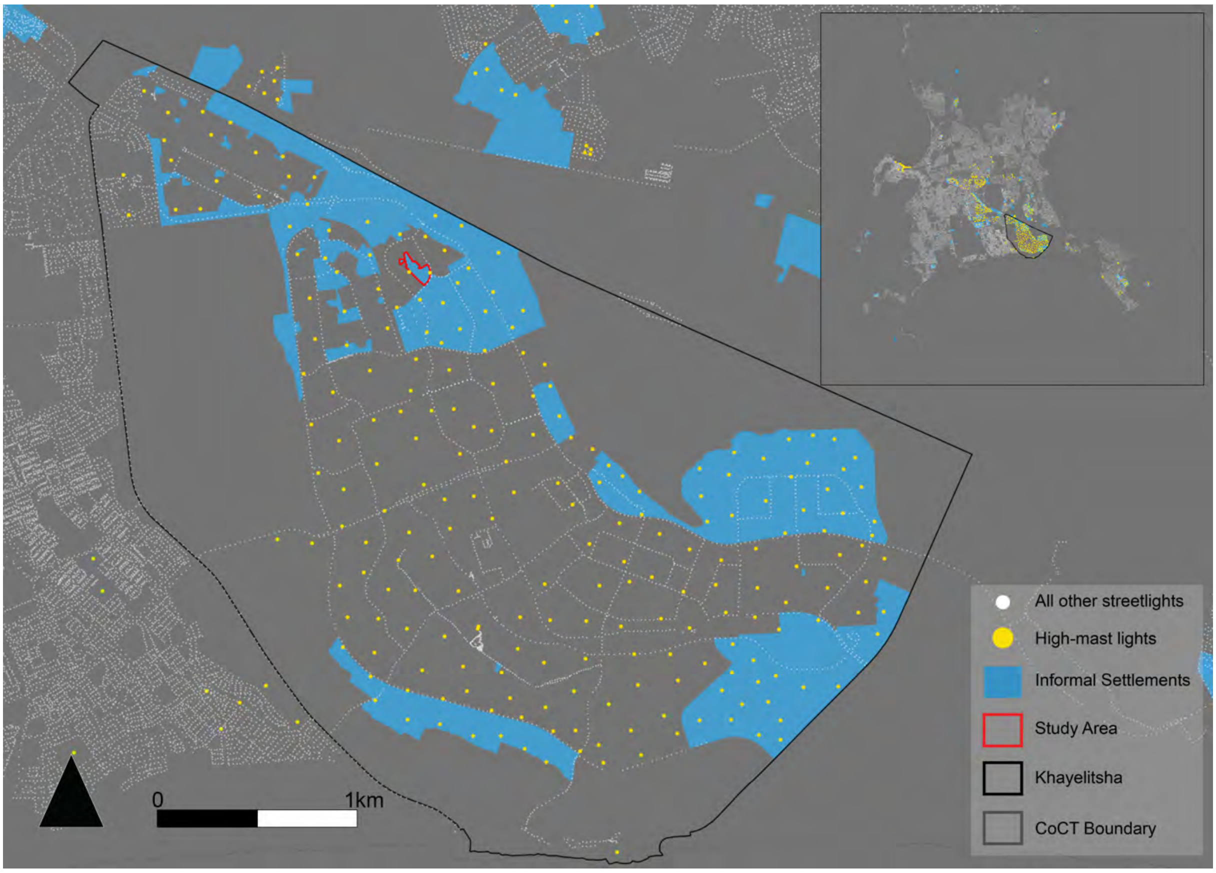
The informal settlement studied in this paper is located on the outskirts of the City of Cape Town, in the northern part of Khayelitsha (Figure 1). Approximately 14% of households in Cape Town live in one of the City of Cape Town's many informal settlements (van der Westhuizen, 2017) and many of these households are located in Khayelitsha, which was zoned as Black African under apartheid. Figure 1 shows the distribution of public lights in Khayelitsha, with larger yellow dots denoting high-mast lights and very small white dots denoting standard streetlighting. In Khayelitsha, the standard streetlights appear to line the main roads, whereas the high-mast lights are distributed in both formal and informal residential areas. In contrast, the area adjacent has far more densely located standard streetlights. Indeed, the density of high-mast

[23] The average lux on the low-volume traffic residential streets near where I live in Zurich is 3-4 lux.

[24] This value is a for a full moon in perigee, also known as a super moon, therefore on most nights the illuminance provided by the moon is lower. The study by Kyba et al. (2017) refutes the previously commonly held belief that the illuminance provided by a full moon is 1 lux.

lights compared to streetlights and the presence of informal settlements in Khayelitsha is higher than in most other areas of the city (Figure 1, see inset map).

Figure 1. Public Lighting in Khayelitsha, Cape Town

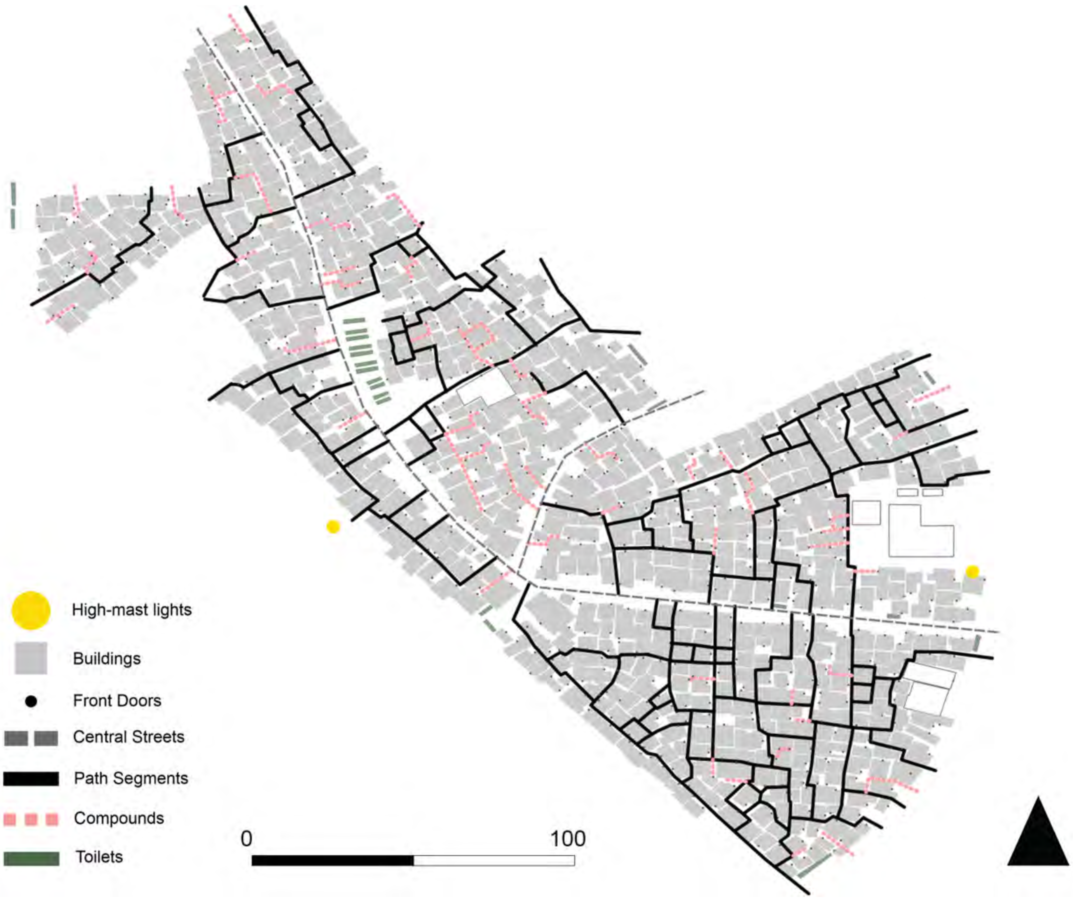


The map shows the distribution of public lighting in the township of Khayelitsha, highlighting the boundary of Khayelitsha (black) and the boundary of the study site (red). High-mast lights are depicted as slightly larger yellow dots, while all other public lights are depicted as very small white dots. Known informal settlements as of 2017 are marked in blue (there are definitely more now). The inset map shows the distribution of public lighting across most of the City of Cape Town, highlighting that in Khayelitsha high-mast lights and informal settlements are co-located, with standard streetlighting lining the main roads, whereas the vast majority of the rest of the City of Cape Town has standard streetlighting with no or few high-mast lights interspersed. Sources: Electricity Public Lighting, City of Cape Town Open Data Portal, 2021; OpenAfrica Cape Town Informal Settlements 2017; Khayelitsha Suburb Boundary, Adrian Frith from SA Census 2011; City of Cape Town Boundary, City of Cape Town Open Data Portal.

The study site (outlined in red in Figure 1) is approximately 30 years old and is surrounded by formal streets and housing on all sides. This site was selected with the help of the local NGO, Social Justice Coalition (SJC), as part of a broader collaborative project investigating the impact of public lighting on life at night.

Figure 2 shows a map of the study site and the immediately surrounding area. The informal settlement is made up of an extremely dense, *ad hoc* network of paths and compounds (semi-private cul-de-sacs) on approximately 38,200 square meters of land and is home to nearly 2,300 people. The vast majority of homes are single story, though the number of double-story homes is slowly increasing. Therefore, most homes are no more than two to three meters tall, thus the buildings are an order of magnitude shorter than a high-mast light. The informal settlement has two high-mast lights located on the perimeter of the settlement (see Figure 2) that are intended to provide light to the entire neighborhood as well as neighboring areas within a radius of about 100 meters of each light. In addition to the high-mast lights, some residents (often business owners) have their own outdoor lights to brighten the area in front of the building (often also their home), however, many of these lights are not working.

Figure 2. Map of the informal settlement



Mapping of the path network and structures done in collaboration with Stephanie Briers, Xolelwa Maha, Thabisa Mfubesi, Frans Mafilika, Noliyema Swartbooi, Tembinkosi Mositata, Thanduxolo Jubati, Pumeza Wanga, Nomsa Siyo, Yamkela Rongwana, Sibongile Mvumvu, and Jennifer Qongo.

4. DATA

To analyze how the relationship between lighting in this informal settlement — predominantly created by high-mast lights — and perception of safety, perception of risk of crime, and willingness to enter public space at night, I use two main types of data: light (lux) measurements and a household survey.[25]

4.1 HIGH-MAST LIGHTS

The locations of public lights in the City of Cape Town are publicly available on the City of Cape Town Open Data Portal. This data has been used to identify the location of the two high-mast lights that serve this informal settlement. In addition, I use it to determine the distance of households to the nearest high-mast light. To calculate this distance, I used QGIS 3.10 A Coruña's Distance to Nearest Hub function to calculate the Euclidean (i.e., as-the-crow-flies) distance in meters between the front door of each building and each of the high-mast lights. For each building I keep the smaller of the two measurements and record which light (western or eastern) is the closest.

I then use distance from the high-mast light as a predictor in order to understand whether it is a good proxy for light measurements, since collecting light measurement data might not be possible in many informal settlements and this measure can be calculated with far less effort, once the location of the high-mast lighting is known.

4.2 LIGHT MEASUREMENTS

To understand the lighting situation throughout the informal settlement, field workers measured the brightness of the lighting (i.e., point horizontal illuminance measured in lux) using a device called an illuminance (light) meter or luxmeter.[26] Since data collection in an informal settlement would be dangerous for someone not sufficiently familiar with the area, a team of six trained residents conducted two rounds of data collection, one in February 2020 (summer) and June 2020 (winter), then one separate round of uniformity measurements in a single path in July 2020.

The following protocol was used to conduct light measurements. Working in teams of two, each pair used an Urceri MT-912 Light Meter to collect *point horizontal* measurements by holding the device horizontally (with the sensor facing upwards) at the height of their belly button (approx. 100-120 cm) and recording both the maximum and minimum value at the front door of

[25] This research was approved by the ETH Zurich Ethics Commission (EK 2019-N-19).

[26] What humans perceive as brightness, is referred to as illuminance. Illuminance is defined as the amount of light falling per unit area of the surface. One lux is equal to one lumen per square meter. (CIE 2007).

each building.[27] If the front door was overshadowed by an awning, the team was instructed to step straight forward from the door until the awning was not overhead, as the intent was to measure the light level when a resident steps into public space. It is common for households to blockade a pathway and install a gate to form a compound of houses that share a semi-private courtyard (see Section 3 and Figure 2). The gates to these compounds are often locked at night. If the gate was locked, the teams took the light measurement at the gate and the same measurement was applied to all households in the compound. In addition, in the June 2020 round, data collectors also took measurements at pre-defined points along paths that did not have many or did not have evenly dispersed front doors. These path points enable us to calculate a path-level average without omitting paths with no front doors.

To ensure data quality, the following protocol was used. All six team members met at the same location each night. They then stood in the same spot and each took a lux measurement in order to calibrate the light meters. The teams of two then worked in a pre-assigned section of the informal settlement. Within each pair, the same team member always operated the light meter and the other always recorded the data on a checklist. To minimize risk to the data collectors, the teams only worked for between one and two hours each night over the course of two weeks.[28]

Given the concerns about keeping data collectors safe, a lighting engineer recommended that the team only collect point horizontal illuminance measurements, since it is the most relevant measure of brightness for this research. This decision is validated by the literature. Svechkina et al. (2020) find that *point horizontal* measurements (in which the device is oriented parallel to the light source) were most effective at predicting feelings of safety in a study in three Israeli cities. Boyce et al. (2019) and Fotios & Castleton (2016) also discuss evidence that indicates *point horizontal illuminance* has a larger effect on perceptions of safety, than other illuminance characteristics. In total, the field team collected measurements for 791 buildings and 103 path points in the informal settlement.

To collect the lux measurements for the uniformity case study, the following protocol was used. First, I selected a case study street that was wide and not too far from a high-mast light (and thus would more likely to be well-lit). Then, based on guidance from a light engineer and the International Commission on Illumination's *Technical Report: Road Lighting Calculations*, which has recommendations for calculations in "areas of irregular shape," I mapped a 30x3-point grid over the path, with a point at every one-meter interval, resulting in 90 measurement points. Using this map as a guide, the team used measuring tape and stones to ensure the 90

[27] The team recorded the maximum and minimum value, rather than just taking one measurement because the measurements can sometimes be noisy. This approach allowed me to check for measurement error by checking that the two measures are not wildly different. In addition, I can then take the average of the two measurements.

[28] Work nights were spaced out more than intended because of load shedding (timed power outages initiated by the utility to manage demand) and because one of the high-mast lights went out, so work could not resume until it was repaired.

measurements were spaced one meter apart and located in the same spot in the path as on the map. Three additional measurements were taken when the path extended substantially more than a meter to the left or right of one of the outside points. One team member was responsible for taking measurements, another for assuring each measurement was taken at the correct location, two for recording the data on a checklist, one for ensuring that no pedestrians walked by while a measurement was being taken, and one took a photo at each row of measurements to enable digitization of the points.

4.3 OUTCOME MEASURES

In March 2019, a household census was conducted in the informal settlement (N = 763), in which one household head or an available adult household member was surveyed.[29] In total, 763 household heads were surveyed and 793 structures counted. Of the remaining buildings, three household heads refused to participate, the occupants of two buildings were not eligible, and the remaining buildings were either empty, no one could be found at the time of the survey, or the building was only for non-residential purposes (e.g., church, childcare, etc.).

The survey instrument contained questions about daytime and nighttime walking preferences, daytime and nighttime activities, perceptions of safety within the informal settlement, perception of risk of crime, and reported experience of crime within the previous 12 months. The survey was offered in English or isiXhosa, the two dominant languages spoken in this neighborhood.

To measure perception of safety, respondents were asked the following questions about their feelings in the informal settlement and nighttime safety measures:[30]

1) What private sources of light do you use when you go outside of your house after sunset?

2) If you must leave your house at nighttime when it is dark, do you carry your mobile phone with you?

3) Do you feel safe when you are outside in your neighborhood during the daytime? (*Options*: Always, most of the time, half of the time, rarely, never)

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[29] In addition to gathering baseline quantitative data for the field experiment, the survey was designed to serve as a formal informal settlement enumeration that contained a count of the number of buildings, residents, businesses, and public services inside the informal settlement, as well as information about structure ownership, access to social grants, and general demographic information. Since numerous organizations throughout the Western Cape (where Cape Town is located) conduct informal settlement enumerations, these elements of the survey instrument were heavily informed by the Western Cape Government Department of Human Settlements Informal Settlements, which sets enumeration guidelines to ensure consistency and comparability. Data from the instrument modules that correspond to the standard recommended enumeration questionnaire were officially submitted to the City of Cape Town's Department of Informal Settlements and Backyarders in February 2020.

[30] I do not create a safety index, as I do with risk of crime and nighttime activities, because I analyze each safety outcome individually.

4) Do you feel safe when you are outside in your neighborhood at night? (*Options:* Always, most of the time, half of the time, rarely, never)

To measure respondents' perception of risk of crime, each respondent received a set of questions asking how big of a risk they think it is that they or someone in their household will be a victim of each of the following crimes in the next year: robbery, gender-based violence, xenophobic violence, burglary, business robbery. Respondents could answer on a scale from one (no risk) to five (very big risk) or they could answer "Don't know." The crime risk index is created by taking the sum over the responses for each crime.[31] I also analyze perceived risk of robbery and perceived risk of burglary separately, since these crimes are most likely to be affected by light availability.

Finally, to measure willingness to engage in public space at night, respondents received the following questions about nighttime activities:

1) How do you use the toilet after sunset (*Options:* Do not need to use the toilet after sunset, Use a bucket inside the structure and empty it after sunrise when it is light outside, Walk to the toilet alone, the same as when it is light outside, Somebody walks with me to the toilet, Other)

2) Yesterday, how many times did you leave the house at night?

3) In the last 7 days, did you go outside at nighttime to spend time with friends or family members? (*Options:* Yes, No friends or family, No)

4) When is the latest time that children/women/men in this household are allowed to be outside in the evening? (*Options:* Half-hour increments between 5 pm and midnight, No specific time, No children/women/men live here)

To create the nighttime activity index, each variable is recoded as binary such that answers corresponding with times during dark hours or activities that require engagement with public space at night are coded as 1, whereas times that occur during daylight or activities that do not require engagement with public space at night are coded as 0. The index is created by taking the sum of each respondent's answers.[32] In addition, I look individually at the relationship between light and questions 1 (use of shared sanitation at night), 2 (leave the house at night, and 3 (go outside at

[31] If a respondent answered "Don't know," the responses was recoded as NA, however, when I calculate the count index I ignore NA's (sum across all other responses) so as not to lose observations.

[32] In creating the count index, NA's are ignored so the sum represents the total of all other responses.

night to spend time with friends or family), as these are the most direct measures of willingness to be in public space at night.[33]

5. EMPIRICAL APPROACH

The methodology has two parts. The first part is the analysis of the lighting levels in the informal settlement. I first calculate each front door lux measurement by taking the average of the minimum and maximum lux measurement at each measurement point from both the February and June 2020 data collections, thereby accounting for the fact that the western high-mast light was not fully functional in February and the eastern high-mast light was not fully functional in June (for path points, the average is only from June). I then use these values to compute a path or compound level average for each path/compound (N = 168) in the informal settlement.

Finally, I categorize the light levels as low, medium, and high based on the literature about how much public light is sufficient (see Section 2). I define "low" as measurements below 2 lux, which is informed by Boyce (2019) who finds that 2 lux is the minimum level required to ensure safe movement. To define the "medium" category, I pull from three sources: Fotios & Castleton (2016) suggests horizontal illuminances between 3-5 lux are sufficient for pedestrians to feel reassured on paths at night, Svechkina et al. (2020) find respondents report high levels of feelings of safety between 5-10 lux, meanwhile the South African standard states that 10 lux is the minimal average horizontal illuminance for wholly pedestrian streets in the city center. Therefore, I define the medium lighting category as being greater than or equal to 2 lux and less than 10 lux. Measurements greater than or equal to 10 lux are in the "high" lighting category. Using these categories, it is possible to map the distribution of light levels throughout the informal settlement by structure.

To study the uniformity of high-mast lighting, I first map the light measurements collected on the case study path (see Section 6.2). Uniformity (U_0) is a measure of the distribution of light in a given space (e.g., a path). It is calculated by computing the ratio of the minimum measurement taken in the study area to the average of all the measurements taken (CIE 2007).

To compute the minimum and the average over all the points, I first calculate the average measurement at each point (based on the two measurements taken and recorded by the data collectors), so that I have a single value for each point. Due to a substantial number of zeroes in the data, however, it is not possible to compute a valid measure of uniformity since U_0 will be equal to 0. Therefore, I plot the points on a map and discuss the visual pattern.

[33] The survey instrument also contained a question about whether residents use shared water taps at night, however, since the vast majority of people have built informal water connections inside their home or yard, this question would not yield a good measure of willingness to go outside at night and is not included.

The second part of the analytical approach is the analysis of the relationship between lighting and three broad outcomes of interest: perception of safety, perception of risk of crime, and willingness to engage in public space at night. To estimate the effect of light levels in the informal settlement, I use ordinary least squares regression of the outcomes of interest on one of four types of predictors: path-level average lux, the lux categories (low is the reference category), distance (meters) from the nearest high-mast light, or distance categories, which approximately correspond to the spatial distribution of the lux categories.

In addition, I control for a vector of respondent characteristics, including gender, age, length of residence (years), and previous victimization in the preceding year (Kaplan & Chalfin, 2021). Similar to Kaplan and Chalfin (2021), I report estimates from ordinary least squares regression to make interpretation simpler, then re-estimate the main analysis using binary or ordinal logistic regression and report the average marginal effects in Appendix C Tables 3-5. I find the results are very similar to estimates based on the OLS regressions.

Specifically, I estimate the following equation:

$$OUTCOME_{ip} = \beta_0 + \beta_1\delta_p + \beta_2 X'_{ip} + \epsilon_{ip} \quad (1)$$

Where $OUTCOME_{ip}$ is the outcome value measured for household i living on the path segment or compound p; δ_p is the average lux measured for a path segment or compound or the lux categories, depending on whether the continuous or categorical version of the variable is used. δ_{ip} replaces δ_p if distance from the high-mast light (or the distance categories) is the predictor. X'_{ip} is a vector of respondent covariates including respondent age, gender, length of residence (years) (Roman & Chalfin, 2008), and previous victimization (Kaplan & Chalfin, 2021); and ϵ_{ip} is the standard error clustered at the path segment/compound level to account for within-path dependence in the error term.

6. RESULTS

6.1 ILLUMINANCE OF HIGH-MAST LIGHTING IN THE INFORMAL SETTLEMENT

Figure 3 visualizes the lux measurements (by structure), categorized as low (0-1.99 lux), medium (2-9.99 lux), and high (10 lux or higher). The average front door measurement is 2.68 lux (*sd* = 9.10, *N* = 791, *min* = 0, *max* = 154.66), which includes all buildings in the settlement no matter whether they responded to the survey or not.[34] Zeroes make up 49.9% of the front door measurements. From visual inspection, it is clear that lighting is not distributed randomly, but rather it is brighter for those living closest to one of the two high-mast lights — more or less in an arc around the light — compared to those living farther. The most consistent dark spots are in the

[34] Two buildings that counted during the household survey no longer existed by the time the light measurements were collected. These numbers do not include the path points because those measurements are not shown in the map.

northern part of the settlement, which is relatively far from both high-mast lights, and in the south-eastern (bottom-right) corner. The structures that have medium or high lux levels, but are far from the high-mast lights, most likely have a private, outdoor light installed on their house. Looking at the main group of toilet blocks near the center of the neighborhood, it appears that the light from the nearest high-mast light is at the end of its range. Five additional toilet blocks also appear to be out of range of both high-mast lights.

Figure 3. The distribution of lux measurements in the informal settlement

The average lux measurement amongst the sample of respondents only (not including any buildings where no survey was done) is 2.72 lux and the average path-level lux measurement is 2.68 lux (N = 168), which includes path point measurements. When I analyze the relationship between distance from the nearest high-mast light and the individual lux measurements, I find they are negatively correlated ($p < 0.01$, $R^2 = 0.06$), such that, as expected, as distances from the high-mast light increases lux measurements decrease (see Appendix C Table 1).

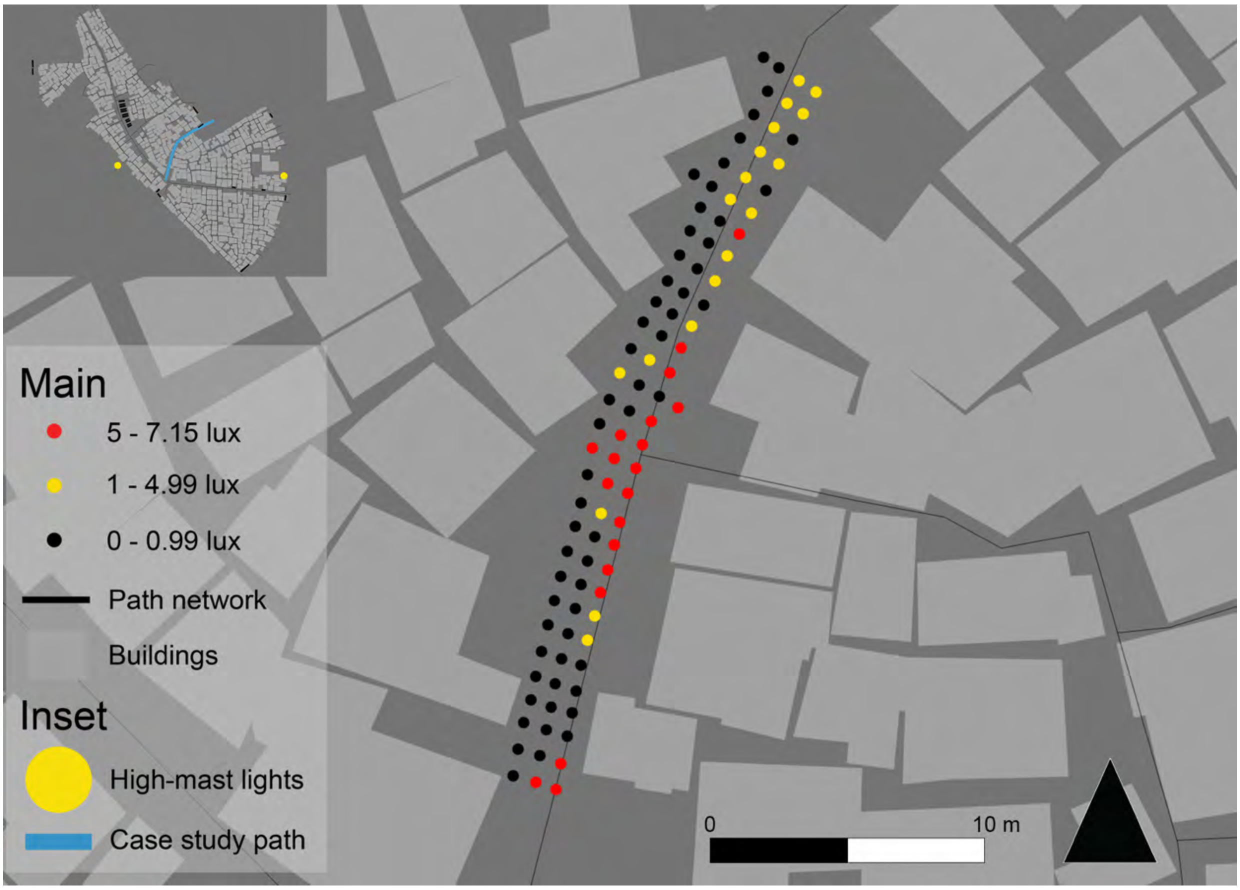
6.2 UNIFORMITY OF HIGH-MAST LIGHTING IN ONE STREET

Figure 4 shows the distribution of uniformity measurements.[35] The entire case study path is approximately 96 meters long and varies in width, while the section I measure is 30 meters long. The first row of three measurement points (bottom-middle of Figure 4) is approximately 91 meters from the nearest high-mast light and the last row of four points (top middle of Figure 4) is approximately 123 meters away (Manhattan distance), but only 60 meters and 75 meters away, respectively, as-the-crow-flies (Euclidean). The case study average is 2.09 lux (sd = 2.47, min = 0, max = 7.15). In total, 27 measurements are equal to zero (29%) and more than half (56) are below 1 lux.[36]

[35] I use different categories in Figure 4 because the maximum lux measurement is below 10 lux on the case study path, thus the categorization used in Figure 3 and for the analysis would not make sense.

[36] The light meter used for data collection was not a professional level light meter due to fears of increasing risk to the data collectors, therefore our light meter is more likely to report 0 lux when the true lux value is actually somewhere between 0 and 1. After zero, the next smallest value in the case study dataset is 0.2 lux.

Figure 4. Categorized measurements from the uniformity case study



The uniformity measurements are categorized differently than the overall lux measurements because the maximum value measured on this path is 7.15 lux. Therefore, the "low" category is 0-0.99 lux, the "medium" category is 1-4.99 lux, and the "high" category is 5-7.15 lux.

According to the CIE (2007) the minimum acceptable value for U_0 is 0.2 lux. However, since so many of the points are 0 lux, calculating U_0 does not provide much information. Instead, visual inspection of Figure 4 is more useful. The large number of zeroes interspersed with higher measurements primarily on the right side of path indicates that even without a valid measure of uniformity, the lighting is not uniform. Thus, even on a relatively wide thoroughfare, where many of the houses have medium or high lux measurements when the measurement was taken at the front door (see Figure 3), there are clear bright spots and dark shadows that hinder visibility.

6.3 INFORMAL SETTLEMENT CHARACTERISTICS

Table 1 reports the summary statistics for respondent characteristics and key outcome variables. In our survey sample (N = 763), more than half of respondents are female and the average age is about 39 years old. On average, respondents have lived in the informal settlement for 17 years, which seems long given how many people think of informal settlements as temporary living arrangements. Paths in the informal settlement are narrow on average, at roughly 1.57 meters.[37]

The bottom panel reports the summary statistics for our main outcomes of interest, as well as the additional variables that make up the previous victimization control variable. There is almost a full point difference between average feelings of safety in the informal settlement during the day, compared to at night, with the lower score reflecting perceived safety at night. Just over half of respondents go outside at night without carrying any private light along and only 37% carry a mobile phone with them. It is possible that those carrying a mobile phone may also be using it as a private source of light.

Similarly, residents report differences in their perception of the risk of various crimes. Residents perceive the highest risk of robbery (mean: 4.36) and burglary (mean: 4.46), while they perceive the lowest risk of xenophobic violence (mean: 2.65) and gender-based violence (mean: 2.79). Due to instances of xenophobic violence elsewhere in South Africa at the time, the household survey did not ask about nationality, however, based on discussion with the leaders the vast majority of residents in this informal settlement are likely of South African origin. Some respondents told surveyors they perceived a risk of xenophobic violence by foreigners *against* South Africans when giving their answer, hence why the average seems higher than expected if most of the community is truly not from another country.

Finally, perceived risk of robbery may be linked to previous victimization —about 25% of respondents said they or someone in their household had been the victim of a robbery in the previous year. There was no question about experience of burglary in the previous year, however 14% reported their house had been vandalized and 11% reported they had been physically attacked. In total, 50% of respondents reported that they or a household member experienced at least one of these three crimes in the previous year.

[37] Since it is not really comparable to measure compound width, I only have measurements for paths in the informal settlement. Measuring path width is very difficult as the width of a given path can change a lot, even within a short distance, therefore I only use the data in the summary statistics to give a sense of path width and do not use it in the analysis.

Table 1. Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Female	763	0.57	0.50	0	1
Age	763	39.12	11.73	15	119
Length of residence	762	16.71	10.59	0	102
Level of education[a]	760	5.40	1.86	0	9
Household income[b]	719	3.13	1.82	0	6
Average lux (household)	763	2.72	9.25	0	155
Average lux (path/compound)	168	2.68	3.45	0	17
Distance from the HML	763	87.73	34.67	4.75	188.10
Path width (cm)	131	157.91	70.02	11.50	549.50
Perception of Safety					
Feel safe outside in neighborhood during day	763	2.64	1.73	1	5
Feel safe outside in neighborhood at night	763	1.76	1.41	1	5
Carries no private light outside at night	763	0.54	0.50	0	1
Carries mobile phone outside at night	740	0.37	0.48	0	1
Perceived Risk of Crime Index (max = 25)	763	17.45	4.42	1	25
Risk of robbery	755	4.36	1.07	1	5
Risk of gender-based violence	726	2.79	1.50	1	5
Risk of xenophobic violence	736	2.65	1.49	1	5
Risk of burglary	757	4.46	0.91	1	5
Risk of business robbery	752	3.56	1.59	1	5
Experience of Crime Index (max = 3)	763	0.50	0.79	0	3
Robbery	755	0.25	0.44	0	1
Vandalism	755	0.14	0.35	0	1
Physical attack	759	0.11	0.31	0	1
Night Activity Index (max = 6)	763	2.30	1.28	0	6
Leave house to use shared sanitation at night	741	0.46	0.50	0	1
Leave house at night for any reason	743	0.77	0.97	0	4
Spend time with friends/family at night	763	0.48	0.50	0	1
Time kids come in for the night	432	19.30	1.33	17.50	23
Time women come in for the night	556	19.71	2.18	17	24
Time men come in for the night	518	20.71	2.09	17	24

Notes: [a]The mean level of education corresponds with achievement of between Grade 10 and Grade 11. [b]The mean income level corresponds with a value between "801-1500 ZAR" (3) and "1501-3500 ZAR" (4). When questions ask about daytime they always refer to the hours between 6 am and 8 pm. When questions ask about nighttime they always refer to the hours between 8 pm and 6 am. All risk question asked about the risk of the event occurring to the respondent or someone in the respondent's family in the next year. Respondents could answer on a scale from 1 (Not a risk) to 5 (Very big risk) or they could choose "Don't know," which was coded as NA. Times are reported in the summary statistics as hours or half-hours, but in the night activity index these variables are recoded as binary, such that dark hours are coded as 1 and daylight hours are coded as 0.

6.4 LIGHT AND NIGHTTIME LIFE

Tables 2 and 3 report the OLS regression results of the key outcomes of interest on average path-level lux (Panel A) and on distance from the high-mast light (Panel B). All regressions control for gender, age, length of residence, and experience of crime in the preceding year.

I find no effect of average path-level lux (continuous) on perception of safety in the informal settlement during the day or at night, in which both outcome variables range from 1-5 (Table 2, columns 1 and 3). In columns 2 and 4, I replace average path-level lux with the lux categories described in Section 5. There is no significant effect of Level 2 (2-9.99 lux) on perception of safety during the day or night, however, Level 3 (10 lux or greater) is associated with a significant increase in safety at night only ($p < 0.05$). The increase, about half a scale point, is reasonably large, as it cuts in half the gap between the nighttime and daytime average perception of safety in the sample.

In addition to reported feelings of safety, I also consider two nighttime behaviors that can be thought of as protective measures taken in response to perception of safety: whether the respondent carries their mobile phone when they go out at night, and whether the respondent carries a private light (e.g., flashlight) when they go out at night. While there is no association between average path lux and both of these behaviors, where lux levels are the predictor (columns 6 and 8), respondents living in Level 3 paths or compounds are 17 percentage points more like to carry a phone outside at night compared to those living in a Level 1 (less than 2 lux) area ($p < 0.05$).

Table 2 Panel B reports the results of OLS regressions with the same outcomes and control variables, however, distance in meters to the nearest high-mast light replaces average lux as the predictor. Similar to Panel A, I include distance both as a continuous variable as well as a categorical variable, with the following distance categories that correspond approximately to the lux categories: far (100 meters or more away, the reference category), medium distance (60-99 meters away), or near (less than 60 meters away). I find no effect of distance to the nearest high-mast light, using either variable type, on perception of safety during the day (columns 1-2). I find a significant negative effect ($p < 0.05$) on respondents' perception of safety at nighttime, indicating that perception of safety decreases for every additional meter away from the nearest high-mast light (column 3). When the distance categories are used instead, both being in the near ($p < 0.05$) and the medium-distance ($p < 0.01$) categories are positively associated with perception of safety at night and the coefficient is similar in size for both groups (about a third of a scale point).

When it comes to protective behaviors, there is a small, negative effect of the distance to the nearest high-mast light on whether respondents report carrying a mobile phone outside at night (column 5, $p < 0.05$). When the distance categories are included instead, it becomes clear the effect is driven by those living nearest to the high-mast light, such that this group is more likely (14.9 percentage points) to carry a mobile phone at night compared to the respondents living more than 100 meters away (column 6, $p < 0.01$). I find no effect of distance from the high-mast light on whether or not respondents report carrying a private source of light outside at night.

I find no association between either lux or distance to the nearest high-mast light on perceived risk of crime. Results are reported in Appendix C Table 2.

Table 2. Perceived safety results

	Safe in Day		Safe at Night		Mobile		No Light	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Avg. Path Lux	0.015		0.022		0.009*		0.008	
	(0.015)		(0.019)		(0.005)		(0.005)	
Female (=1)	-0.554***	-0.551***	-0.473***	-0.463***	-0.263***	-0.261***	0.067*	0.066*
	(0.119)	(0.120)	(0.098)	(0.099)	(0.040)	(0.040)	(0.036)	(0.036)
Age	-0.005	-0.005	-0.007	-0.007	-0.004***	-0.004***	0.002	0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)
Length of Residence (yrs)	-0.014**	-0.014**	-0.007	-0.007	-0.002	-0.002	-0.001	-0.001
	(0.006)	(0.006)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Prev. Victim (=1)	-0.397***	-0.399***	-0.261***	-0.266***	-0.010	-0.012	-0.036	-0.036
	(0.114)	(0.114)	(0.096)	(0.096)	(0.041)	(0.040)	(0.036)	(0.036)
Lux Level 2		0.011		-0.069		0.001		0.032
		(0.126)		(0.097)		(0.032)		(0.041)
Lux Level 3		0.254*		0.554**		0.172**		0.072
		(0.131)		(0.262)		(0.073)		(0.062)
(Intercept)	3.488***	3.510***	2.444***	2.501***	0.694***	0.711***	0.432***	0.436***
	(0.210)	(0.209)	(0.214)	(0.211)	(0.067)	(0.067)	(0.070)	(0.070)
Mean	2.640	2.640	1.760	1.760	0.370	0.370	0.540	0.540
Adj. R2	0.041	0.040	0.039	0.045	0.090	0.091	0.005	0.002
Num. obs.	762	762	762	762	739	739	762	762
Clusters	168	168	168	168	167	167	168	168
Panel B								
Dist. Nearest HML (m)	-0.001		-0.003**		-0.001**		0.000	
	(0.002)		(0.001)		(0.001)		(0.000)	
Female (=1)	-0.557***	-0.557***	-0.479***	-0.484***	-0.264***	-0.264***	0.066*	0.064*
	(0.120)	(0.120)	(0.099)	(0.099)	(0.039)	(0.039)	(0.036)	(0.036)
Age	-0.005	-0.004	-0.006	-0.006	-0.004**	-0.004**	0.002	0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
Length of Residence (yrs)	-0.014**	-0.015**	-0.008	-0.008	-0.002	-0.002	-0.001	-0.001
	(0.006)	(0.006)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Prev. Victim (=1)	-0.390***	-0.388***	-0.244**	-0.239**	-0.004	-0.005	-0.037	-0.033
	(0.114)	(0.114)	(0.095)	(0.095)	(0.040)	(0.040)	(0.036)	(0.036)
Med: Between 60 & 100 ms		0.086		0.325***		0.058		0.056
		(0.132)		(0.118)		(0.038)		(0.046)
Near: 60 ms or less		0.197		0.334**		0.149***		0.028
		(0.169)		(0.140)		(0.048)		(0.049)
(Intercept)	3.624***	3.427***	2.766***	2.242***	0.832***	0.647***	0.427***	0.412***
	(0.244)	(0.236)	(0.238)	(0.222)	(0.087)	(0.069)	(0.081)	(0.073)
Mean	2.640	2.640	1.760	1.760	0.370	0.370	0.540	0.540
Adj. R2	0.041	0.040	0.043	0.047	0.096	0.096	0.002	0.003
Num. obs.	762	762	762	762	739	739	762	762
N Clusters	168	168	168	168	167	167	168	168

Note: Robust standard errors clustered at the path/compound level. In regressions where the lux categories are the predictors, the left out group is Lux Level 1 (0 - 1.99 lux). In regressions where distances categories are the predictors, the left out group is Far (100 meters+). For both questions about perception of safety, respondents could answer on a scale from Never (1) to Always (5). ***p < 0.01; **p < 0.05; *p < 0.1.

In Table 3, I find no association between average path-level lux or distance from the nearest high-mast light on the nighttime activity index or any of the individual outcomes. When I use binary or ordinal logistic regression to test all the same relationships, the only difference is that middle-distance group is significantly more likely to leave the house at night, though the effect diminishes above two times per night. The average marginal effects are reported in Appendix C Tables 3-5.

Being female is negatively associated with perception of safety at both times of day, carrying a mobile phone outside at night, the nighttime activity index, using shared sanitation at night, and frequency of leaving the house at night, but not with any other outcomes, indicating that women feel less safe in general and participate in fewer nighttime activities.

There is no association between age and perception of safety (Table 2, columns 1-4) or the use of shared sanitation at night (Table 3, columns 3-4), but there is a negative association between age and carrying a mobile phone at night (Table 2, columns 5-6), the nighttime activity index, and going out with friends and family at night (Table 3, columns 1-2 and 7-8). These results suggest that as people get older, they engage in fewer nighttime activities, which could be linked to care responsibilities. I find a negative effect of length of residence on perception of safety during the day (Table 2, columns 1-2, $p < 0.05$) and on frequency of leaving the house at night (Table 2, columns 5-6, $p < 0.05$). In addition, previous victimization is negatively associated with perception of safety at both times of day, but there is no relationship with any measure of nighttime activity, indicating that experience of a crime in the preceding year is associated with decreased perception of safety, but may not influence behavior.

Table 3. Willingness to engage in public space at night results

	Night Activity Index		Shared Sanitation		Leave House		Out w/ Friends/Fam	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A				
Avg. Path Lux	0.013		-0.009		0.021		-0.005	
	(0.016)		(0.006)		(0.014)		(0.006)	
Female (=1)	-0.168*	-0.168*	-0.120***	-0.120***	-0.184**	-0.187**	-0.043	-0.044
	(0.088)	(0.088)	(0.036)	(0.036)	(0.074)	(0.074)	(0.031)	(0.031)
Age	-0.017***	-0.017***	-0.001	-0.001	-0.008*	-0.007*	-0.006***	-0.006***
	(0.005)	(0.005)	(0.002)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)
Length of Residence (yrs)	0.001	0.001	-0.002	-0.002	0.007**	0.007*	-0.001	-0.001
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
Prev. Victim (=1)	0.137	0.136	0.075**	0.076**	-0.001	0.000	0.018	0.019
	(0.093)	(0.093)	(0.037)	(0.037)	(0.071)	(0.071)	(0.043)	(0.043)
Lux Level 2		0.056		-0.050		0.129		0.006
		(0.086)		(0.044)		(0.084)		(0.035)
Lux Level 3		0.143		-0.136		0.153		-0.047
		(0.255)		(0.108)		(0.198)		(0.092)
(Intercept)	2.974***	2.979***	0.616***	0.616***	1.001***	0.997***	0.764***	0.754***
	(0.186)	(0.184)	(0.069)	(0.068)	(0.141)	(0.136)	(0.067)	(0.067)
Mean	2.300	2.300	0.460	0.460	0.770	0.770	0.480	0.480
Adj. R2	0.028	0.026	0.025	0.025	0.017	0.014	0.021	0.019
Num. obs.	762	762	740	740	742	742	762	762
N Clusters	168	168	166	166	167	167	168	168
				Panel B				
Dist. Nearest HML (m)	-0.001		-0.000		-0.001		0.000	
	(0.002)		(0.001)		(0.001)		(0.001)	
Female (=1)	-0.171*	-0.175**	-0.119***	-0.123***	-0.188**	-0.192**	-0.043	-0.041
	(0.089)	(0.089)	(0.036)	(0.036)	(0.075)	(0.075)	(0.031)	(0.031)
Age	-0.017***	-0.017***	-0.001	-0.001	-0.007*	-0.007*	-0.006***	-0.006***
	(0.005)	(0.005)	(0.002)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)
Length of Residence	0.001	0.002	-0.002	-0.002	0.007*	0.007*	-0.001	-0.001
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
Prev. Victim	0.142	0.138	0.076**	0.076**	0.008	0.009	0.017	0.014
	(0.094)	(0.094)	(0.038)	(0.038)	(0.072)	(0.072)	(0.042)	(0.042)
Med: Between 60 & 100 m		0.121		0.069		0.161*		-0.064
		(0.104)		(0.045)		(0.081)		(0.047)
Near: 60 ms or less		-0.122		-0.051		0.096		-0.073
		(0.131)		(0.057)		(0.106)		(0.047)
(Intercept)	3.076***	2.966***	0.614***	0.575***	1.158***	0.935***	0.737***	0.806***
	(0.210)	(0.191)	(0.080)	(0.070)	(0.150)	(0.155)	(0.071)	(0.073)
Mean	2.300	2.300	0.460	0.460	0.770	0.770	0.480	0.480
Adj. R2	0.027	0.031	0.022	0.030	0.014	0.015	0.020	0.023
Num. obs.	762	762	740	740	742	742	762	762
N Clusters	168	168	166	166	167	167	168	168

Note: Robust standard errors clustered at the path/compound level. In regressions where the lux categories are the predictors, the left out group is Lux Level 1 (0 - 1.99 lux). In regressions where distances categories are the predictors, the left out group is Far (100 meters+).The night activity index is made up of six binary variables: whether respondents leave the house at n ight to use shared sanitation, whether they leave the house at night at all, whether they spent time with family/friends in the previous week, whether men, women, and children come in for the night after dark. The count index ranges from 0 - 6. The frequency with which respondent report leaving the house at night (columns 5 and 6) is ordinal when it is an individual outcome, which ranges from 0 (never) - 4 (more than 3 times per night). ***p < 0.01; **p < 0.05; *p < 0.1.

6.6 HETEROGENEITY

I look at heterogeneous effects with respect to gender since I find that gender is frequently associated with perceived safety and willingness to engage in public space at night and since several other studies find that gender moderates the relationship between nighttime light and these outcomes (e.g., Blöbaum and Hunecke, 2005; Boomsma and Steg, 2014).

Interacting the light categories with being female, I find no difference between men and women associated with light levels (Table 4, Panel A). When I interact the distance categories with being female, I find that living nearest to the high-mast light increases men's perception of safety at both times of day, but not women's (Table 4, Panel B, columns 1-2). Otherwise, for the remaining outcomes, I find no heterogeneous effects.

Table 4. Heterogeneity results

	Safe in Day	Safe at Night	Mobile	No Light	Crime Risk Index	Robbery Risk	Burglary Risk	Night Activity Index	Shared Sanitation	Leave House	Out Friends/ Family
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A											
Lux Level 2	0.142	0.046	-0.042	0.018	-0.228	-0.162	-0.017	-0.007	-0.020	0.051	-0.004
	(0.202)	(0.180)	(0.064)	(0.068)	(0.474)	(0.116)	(0.100)	(0.111)	(0.054)	(0.118)	(0.047)
Lux Level 3	0.271	0.609***	0.130	0.029	0.271	-0.085	-0.234	0.101	-0.070	0.084	-0.088
	(0.274)	(0.205)	(0.090)	(0.118)	(0.997)	(0.249)	(0.214)	(0.284)	(0.157)	(0.253)	(0.104)
Female (=1)	-0.472***	-0.389***	-0.291***	0.053	0.041	-0.098	-0.019	-0.210*	-0.094*	-0.241**	-0.055
	(0.165)	(0.145)	(0.058)	(0.044)	(0.418)	(0.087)	(0.089)	(0.117)	(0.050)	(0.095)	(0.045)
Level 2*Female	-0.224	-0.198	0.075	0.025	0.488	0.189	-0.040	0.107	-0.051	0.133	0.017
	(0.244)	(0.202)	(0.081)	(0.081)	(0.609)	(0.122)	(0.120)	(0.184)	(0.067)	(0.147)	(0.059)
Level 3*Female	-0.022	-0.100	0.077	0.086	0.785	0.304	0.352	0.079	-0.130	0.128	0.082
	(0.563)	(0.323)	(0.131)	(0.152)	(1.058)	(0.316)	(0.213)	(0.208)	(0.126)	(0.184)	(0.137)
(Intercept)	3.484***	2.446***	0.724***	0.436***	17.358***	4.307***	4.425***	4.212***	0.596***	1.033***	0.773***
	(0.214)	(0.216)	(0.069)	(0.070)	(0.608)	(0.150)	(0.127)	(0.208)	(0.070)	(0.149)	(0.067)
Adj. R2	0.038	0.044	0.090	0.000	-0.000	-0.005	-0.007	0.024	0.024	0.013	0.017
Num. obs.	762	762	739	762	762	754	756	762	740	742	762
N Clusters	168	168	167	168	168	167	168	168	166	167	168
Panel B											
Med: 60-100 m	0.139	0.382**	0.097	0.058	0.851	0.005	-0.099	0.182	0.183***	0.056	-0.065
	(0.191)	(0.169)	(0.071)	(0.068)	(0.520)	(0.133)	(0.107)	(0.186)	(0.055)	(0.131)	(0.061)
Near: 60 m or less	0.581**	0.679***	0.252***	-0.036	-0.299	-0.328*	-0.273**	0.125	0.011	-0.019	0.030
	(0.230)	(0.246)	(0.093)	(0.071)	(0.635)	(0.187)	(0.122)	(0.176)	(0.084)	(0.159)	(0.064)
Female (=1)	-0.357*	-0.298*	-0.190**	0.039	-0.505	-0.133	-0.118	-0.058	-0.006	-0.322**	0.000
	(0.182)	(0.151)	(0.075)	(0.074)	(0.400)	(0.100)	(0.096)	(0.188)	(0.063)	(0.130)	(0.062)
Med*Female	-0.104	-0.110	-0.072	-0.001	0.775	0.142	0.092	-0.097	-0.201**	0.186	-0.002
	(0.304)	(0.209)	(0.091)	(0.094)	(0.628)	(0.145)	(0.149)	(0.246)	(0.077)	(0.154)	(0.086)
Near*Female	-0.688**	-0.619**	-0.184	0.116	1.625*	0.207	0.292	-0.412	-0.115	0.208	-0.184*
	(0.281)	(0.265)	(0.124)	(0.091)	(0.839)	(0.165)	(0.183)	(0.266)	(0.109)	(0.176)	(0.103)
(Intercept)	3.322***	2.143***	0.609***	0.424***	16.924***	4.339***	4.538***	4.043***	0.507***	1.008***	0.785***
	(0.237)	(0.226)	(0.079)	(0.086)	(0.644)	(0.157)	(0.131)	(0.220)	(0.075)	(0.172)	(0.075)
Adj. R2	0.044	0.051	0.099	0.003	0.018	0.005	-0.005	0.026	0.035	0.015	0.026
Num. obs.	762	762	739	762	762	754	756	762	740	742	762
N Clusters	168	168	167	168	168	167	168	168	166	167	168

Note: Robust standard errors clustered at the path/compound level. Control variables include: age, length of residence, and previous victimization. ***p < 0.01; **p < 0.05; *p < 0.1.

Finally, since I specify lux categories based on literature that is as yet still inconclusive, I change the lux level categories so that "low" is defined as 0-0.99 lux, "medium" is defined as 1-4.99 lux, and "high" is any value greater than or equal to 5 lux.[38] These new categories reflect Fotios & Castleton's (2016) suggestion that 3-5 lux is sufficient for pedestrians to feel reassured outside at night.. The "low" category is cut off just below 1 lux instead of 2 lux to try to capture the paths that are truly dark and well below the 2 lux that Boyce (2019) suggests is sufficient for visibility.

For the safety outcomes, I find that changing the lux category definitions does change the results. Level 3 was significantly associated with the perception of safety at night in the main results, but with the new categorization it is not significant (Appendix C Table 6, column 2). This change in the results suggests that by relaxing the light threshold Level 3 now includes more respondents who do not feel as safe. In addition, in the main results Level 3 was associated with more respondents reporting that they did not engage in protective behavior, like leaving their mobile phone at home, however, this effect essentially disappears (column 3). All results with the adjusted lux levels are reported in Appendix C Table 6.

7. DISCUSSION

To my knowledge, this study represents the first field assessment of light levels in an informal settlement and the first analysis of how those light levels and public lighting infrastructure influence the experience of life at night. I find evidence that light levels in this informal settlement are low on average and highly unevenly distributed, with a spatial pattern that leads to high lux measurements in roughly a 60-meter radius around each high-mast light, middle range measurements within 100 meters of the light, and very little or no light at all for residents who live more than 100 meters away. In addition, even on a wide, vehicle-accessible street close to a high-mast light, light levels are not uniform within the street. Given that South Africa's lighting standards do not have specifications relevant to the streets and pedestrian pathways in informal settlements, it is not possible to quantify how short the lighting levels in this neighborhood are of the standard, but it is clear the quality of public lighting is poor. As Wu & Kim (2018) find, evenly bright light and even darkness are preferable to large differentials between light and dark areas because it is less fatiguing for the human eye.

The question then is how such lighting infrastructure affects life at night in this urban neighborhood and how policymakers should think of high-mast lights when assessing public lighting solutions. Although many other studies seek to evaluate the relationship between streetlights and perceptions of safety, perceived risk of crime, and nighttime activity (see Section 2), none of these studies focus on informal settlements where the light levels vary so intensely (and perhaps, unintentionally) within one contiguous neighborhood. First, while much of the literature from formal cities finds a strong link between perception of safety and light levels (e.g., Kaplan

[38] These are the same categories used in Figure 4.

and Chalfin, 2021; Painter, 1996), I find a somewhat weak relationship between light and perception of safety at nighttime, as there is only a significant relationship between respondent living on paths with an average lux greater than 10 or for those living within 100 meters of the nearest high-mast light. This finding is different than previous findings (e.g., Fotios and Castleton, 2016; Svechkina et al., 2020), which suggest that beyond 10 lux there are diminishing gains in terms of perception of safety. Furthermore, when the threshold for "high" amount of light drops to 5 lux, the upper boundary suggested by Fotios & Castleton (2016), the effect disappears, indicating that this threshold is too low to be linked to perception of safety at night in this sample.

Interestingly, I also find evidence of a relationship between light levels and one of the protective measures — carrying a mobile phone outside at night — which is an indirect indicator of perception of safety. Leaving a mobile at home at night (to avoid robbery) is a protective measure that residents reported using in informal discussions throughout the fieldwork. However, I only find that residents report carrying a mobile phone if they live on a path that is brighter than 10 lux. One explanation is that respondents living in the brightest areas may feel safer because the areas immediately surrounding them will also tend to be bright, whereas respondents living in areas with less than 10 lux of illumination may be more likely to live near a mix of lit and unlit paths or mostly other unlit paths, increasing their sense that they should take action to improve their safety. That said, since I find no relationship between light level and carrying a light outside at night, it is not clear if this is the case.

When I use distance from the high-mast light as the predictor, the results are slightly different. There is still a significant effect of living closer to the high-mast light on perceptions of safety at night, but the effect is significant for those living closest to the high-mast light as well as those living in the middle-distance group (60-100 meters away). As with the lux level findings, I find those living closer to the high-mast light are more likely to carry a mobile phone, but I still find no association with residents' carrying a private light source outside at night. The more robust association with the safety could suggest that proximity to the infrastructure induces feelings of safety, however, it is not possible to be sure with the available data. It is also possible that distance from the high-mast lights captures other unobserved characteristics.

Much of the literature points to gender as an important modifier of the relationship between light and perceptions of safety (Fotios, Unwin, et al., 2015; Nair et al., 1997; Painter, 1996). While I find that being female is always associated with decreased perception of safety in the main results, I only find significant differences between men and women for respondents living nearest to a high-mast light. Thus, it is not clear how strong of a role being female plays in modifying the relationship between light and safety, however, it is clear that women generally feel less safe than men.

Consistent with a broad discussion in the literature about the difference between perception of safety and fear of crime (which I measure as perceived risk of crime), I find the perception of crime risk results are not similar to the perception of safety results (Rountree & Land, 1996). Indeed, I find no relationship between light levels or distance from the high-mast light on perceived risk of crime. As Lorenc et al. (2014) have suggested, this could be explained by the fact that an individual's perception of the risk of crime has more to do with salience of crime in the area. In addition, I find that residents perceive a rather high risk of crime, on average, especially when it comes to robberies and burglaries, regardless of whether they have been the victim of a crime in the previous year, which is also consistent with the literature (Rountree & Land, 1996).

Finally, I find no effect of light levels on nighttime activity. Fisher & Nasar (1992) argue that urban environments that limit the ability to see for the pedestrian (prospect), enable refuge for a potential offender, and limit opportunities for escape contribute to fear in public space. Therefore, one reason why I find some effects on perception of safety, but they do not appear to translate to engagement in public space could be that those living on the brightest paths are actually more deterred by the uneven light levels in the informal settlement, as most places other than the area where they live are not as well-lit. Thus, this group may say they feel safer than other residents, but due to the strong contrast between where they live and where they might go, they behave no differently than residents living on less well-lit paths. If this interpretation is true, it indicates a serious failure of the high-mast lights as public lighting infrastructure, as it seems that even those people experiencing the best public lighting are not necessarily more willing to go out at night, particularly to access shared sanitation.

These results should be considered in light of several limitations. First, this study suffers from a similar shortcoming as many others in this field in that the findings are merely associational and should not be interpreted as causal in any way. Although the sample is relatively large and the data comes from a real-life scenario (unlike much of the literature), this weakness still influences how much these findings can contribute to our understanding of the relationship between light and the outcomes of interest as there is always the risk of omitted variable bias. A second limitation is the mismatch between the perception of safety question, which asks about safety in the entire neighborhood, and the lux measurements, which are very local (the front door or path where the respondent lives). Since the household survey occurred before it was clear that light measurements would even be possible, the survey questions were not designed to differentiate between perception of safety at different locations within the settlement. As Lorenc et al. (2014) highlight in their meta-review of the relationship between streetlights and perception of safety or fear of crime, "Perceptions of space and the physical environment at a local level may interact with the broader determinants of fear in complex and unpredictable ways." What that means for this analysis is that asking localized questions about perception of safety would have been interesting given the granularity of the lux data. Though it still would have been important to understand perceptions of safety in the neighborhood overall when considering the impact of an infrastructure intervention intended to serve the entire community. Future work would benefit by studying more than one community and asking both local and global questions about perception of safety to better understand the interaction between light levels and perception of safety at different geographic scales.

8. CONCLUSION

This study presents the results of an analysis of the quality and influence of high-mast lighting at night. In the first part of the analysis, I find that that average light levels in the informal settlement I study are low. Using one relatively wide path as a best-case scenario case study, I also find that uniformity is low. Taken together, this assessment indicates that high-mast lighting does not provide effective public lighting. The second part of the study examines how this lighting situation influences perceptions of safety, perceived risk of crime, and willingness to engage in public space at night. Consistent, at least in direction, with much of the literature, I find an association between light levels and perception of safety at night, however, other studies appear to find stronger effects. Similar to several other studies, I also find that women feel significantly less safe, generally, and that living closer to the high-mast light mainly increases the perception of safety of men, but not of women. On the other hand, I find no influence of lighting on perceived risk of crime and no effects on nighttime activities in public space.

While these findings are purely associational, they suggest that the poor quality of the high-mast lighting in this informal settlement may provide minimal benefit in terms of perception of safety, perceived risk of crime, and engagement in public space at night, to the vast majority of residents. Even those living in the brightest areas might feel safer, but still not engage in more nighttime activities. Despite the limitations of this study, there are clear lessons for policymakers considering implementing high-mast lights in informal settlements. First, the results indicate that a lighting standard for informal settlements could be useful in truly understanding the extent of access to public lighting in informal settlements that do have high-mast lights (or streetlights), so that city governments can adequately assess their own service provision. Second, while one major argument in favor of high-mast lights is that they are easier to maintain because they are installed on the perimeter of informal settlement, rather than deep within a dense area, these maintenance cost benefits may be negated by the failure of high-mast lighting to provide enough public light for most residents to feel safe where they live at night and have access to shared sanitation, not to mention the willingness to engage in social activities outside their home at night — which is also important for quality of life. After all, infrastructure maintenance is a second order problem that assumes the infrastructure provides the intended service. If that is not the case, as this study demonstrates, maintenance is a moot point.

9. APPENDIX C

Figure 1. Picture of one of the high-mast lights serving the study site

Table 1. OLS Regression of avg. lux on distance from the nearest high-mast light

	HH Avg. Lux (1)	Path Avg. Lux (2)
Distance HML (m)	-0.064***	-0.035***
	(0.012)	(0.009)
(Intercept)	8.370***	5.739***
	(1.370)	(0.768)
Obs.	763	763
Adj. R^2	0.057	0.122
Clusters	168	168

Notes: Robust standard errors clustered at the path/compound level. *** p < 0.01; ** p < 0.05; * p < 0.1.

Table 2. Perception of risk of crime results

	Crime Risk Index		Robbery Risk		Burglary Risk	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Avg. Path Lux	0.057		-0.002		0.001	
	(0.056)		(0.015)		(0.009)	
Female (=1)	0.253	0.257	-0.017	-0.014	-0.012	-0.012
	(0.304)	(0.305)	(0.068)	(0.067)	(0.062)	(0.063)
Age	-0.009	-0.009	0.000	0.000	0.000	0.000
	(0.014)	(0.013)	(0.003)	(0.003)	(0.003)	(0.003)
Length of Residence	0.028**	0.029**	0.005	0.005	0.001	0.001
	(0.014)	(0.014)	(0.003)	(0.003)	(0.003)	(0.003)
Prev. Victim	-0.459	-0.463	0.057	0.056	0.029	0.029
	(0.380)	(0.382)	(0.089)	(0.088)	(0.062)	(0.062)
Lux Level 2		0.055		-0.053		-0.041
		(0.366)		(0.093)		(0.072)
Lux Level 3		0.670		0.070		-0.063
		(0.707)		(0.164)		(0.130)
(Intercept)	17.218***	17.301***	4.269***	4.282***	4.427***	4.443***
	(0.559)	(0.577)	(0.151)	(0.154)	(0.120)	(0.122)
Mean	17.450	17.450	4.360	4.360	4.460	4.460
Adj. R2	0.003	0.001	-0.004	-0.004	-0.006	-0.007
Num. obs.	762	762	754	754	756	756
N Clusters	168	168	167	167	168	168
Panel B						
Dist. nearest HML (m)	-0.009		0.002		0.001	
	(0.006)		(0.001)		(0.001)	
Female (=1)	0.237	0.206	-0.015	-0.023	-0.011	-0.011
	(0.306)	(0.309)	(0.067)	(0.067)	(0.063)	(0.063)
Age	-0.007	-0.006	-0.000	-0.000	0.000	0.000
	(0.013)	(0.013)	(0.003)	(0.003)	(0.003)	(0.003)
Length of Residence	0.027**	0.028**	0.005*	0.005*	0.001	0.001
	(0.013)	(0.013)	(0.003)	(0.003)	(0.003)	(0.003)
Prev. Victim	-0.412	-0.393	0.049	0.053	0.023	0.025
	(0.376)	(0.377)	(0.087)	(0.089)	(0.061)	(0.062)
Med: Between 60 & 100 ms		1.278***		0.084		-0.049
		(0.427)		(0.095)		(0.075)
Near: 60 ms or less		0.604		-0.214		-0.112
		(0.556)		(0.139)		(0.096)
(Intercept)	18.088***	16.532***	4.140***	4.277***	4.312***	4.481***
	(0.806)	(0.628)	(0.217)	(0.154)	(0.134)	(0.129)
Mean	17.450	17.450	4.360	4.360	4.460	4.460
Adj. R2	0.007	0.016	-0.001	0.007	-0.003	-0.006
Num. obs.	762	762	754	754	756	756
N Clusters	168	168	167	167	168	168

Note: Robust standard errors clustered at the path/compound level. In regressions where the lux categories are the predictors, the left out group is Lux Level 1 (0 - 2 lux). In regressions where distances categories are the predictors, the left out group is Far (more than 100 meters). For the crime risk index, values range from 1 - 25. All individual risk questions had five options ranging from 'Not a risk' (1) to 'Very big risk' (5). 'I don't know' responses were recoded as NA. ***p < 0.01; **p < 0.05; *p < 0.1.

Appendix C Table 2 reports the OLS regression results for the perceived risk of crime index, perceived risk of robbery, and perceived risk of burglary. I estimate risk of robbery and risk of burglary individually because these crimes are most likely to be affected by the availability of public lighting. I find no effect of average path lux or the lux level categories on the perception of crime risk index, robbery risk, or burglary risk. In Panel B, I replace the lux variables with distance to the nearest high-mast light (continuous and categorical). I find no association between distance to the nearest high-mast light and any outcomes.

Table 3. Marginal effects of perceived safety outcomes on lux and distance from the nearest high-mast light

Outcome	Marg. Effect	Std. Error	p-value	Marg. Effect	Std. Error	p-value	Marg. Effect	Std. Error	p-value
Panel A. Lux Measurements	**Predictor: Avg. Path Lux**			**Lux Level 2**			**Lux Level 3**		
Feel safe in the informal settlement during the day		(1)				(2)			
Never	-0.005	0.005	0.292	0.000	0.036	0.991	-0.075	0.067	0.262
Rarely	0.000	0.000	0.999	0.000	0.000	0.995	-0.002	0.004	0.595
About half the time	0.000	0.000	0.306	0.000	0.002	0.991	0.003**	0.001	0.047
More than half the time	0.001	0.001	0.298	0.000	0.005	0.991	0.009	0.007	0.194
Always	0.004	0.004	0.292	0.000	0.029	0.991	0.065	0.062	0.299
Feel safe in the informal settlement at night		(3)				(4)			
Never	-0.008**	0.004	0.048	0.017	0.034	0.615	-0.188**	0.074	0.011
Rarely	0.001*	0.001	0.061	-0.003	0.005	0.619	0.020***	0.006	0.001
About half the time	0.001*	0.001	0.061	-0.002	0.005	0.618	0.022***	0.008	0.005
More than half the time	0.002*	0.001	0.057	-0.003	0.007	0.616	0.036**	0.014	0.010
Always	0.004**	0.002	0.049	-0.009	0.017	0.614	0.109**	0.050	0.028
Carry mobile phone outside at night		(5)				(6)			
Yes	0.009*	0.005	0.057	0.002	0.036	0.952	0.172**	0.077	0.026
Carries no private light outside at night		(7)				(8)			
Yes	0.008	0.005	0.147	0.032	0.038	0.407	0.072	0.077	0.346
Panel B. Distance from the High-mast Light	**Predictor: Distance (m)**			**Mid-distance**			**Near**		
Feel safe in the informal settlement during the day		(1)				(2)			
Never	0.000	0.000	0.530	-0.017	0.038	0.659	-0.048	0.046	0.302
Rarely	0.000	0.000	0.985	0.000	0.000	0.946	-0.001	0.001	0.664
About half the time	0.000	0.000	0.533	0.001	0.002	0.659	0.002	0.002	0.238
More than half the time	0.000	0.000	0.532	0.002	0.005	0.659	0.006	0.006	0.284
Always	0.000	0.000	0.530	0.014	0.031	0.660	0.039	0.039	0.317
Feel safe in the informal settlement at night		(3)				(4)			
Never	0.001***	0.000	0.003	-0.135***	0.039	0.001	-0.155***	0.052	0.003
Rarely	0.000***	0.000	0.008	0.020***	0.006	0.002	0.020***	0.006	0.002
About half the time	0.000***	0.000	0.009	0.019***	0.006	0.003	0.020***	0.007	0.004
More than half the time	0.000***	0.000	0.007	0.028***	0.009	0.002	0.031***	0.011	0.005
Always	-0.001***	0.000	0.003	0.069***	0.021	0.001	0.084***	0.031	0.007
Carry mobile phone outside at night		(5)				(6)			
Yes	-0.001***	0.000	0.003	0.057	0.038	0.132	0.149***	0.047	0.002
Carries no private light outside at night		(7)				(8)			
Yes	0.000	0.001	0.635	0.056	0.041	0.176	0.028	0.050	0.571

Note: The table reports the average marginal effects of either binary or ordinal logit regression. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 4. Marginal effects of perceived crime risk outcomes on lux and distance from the nearest high-mast light

Outcome	Marg. Effect	Std. Error	p-value	Marg. Effect	Std. Error	p-value	Marg. Effect	Std. Error	p-value
Panel A. Lux Measurements	**Predictor: Avg. Path Lux**			**Lux Level 2**			**Lux Level 3**		
Perceived Risk of Robbery	(1)			(2)					
No risk	-0.001	0.001	0.620	0.003	0.008	0.711	-0.012	0.014	0.396
Small risk	0.000	0.000	0.621	0.001	0.004	0.711	-0.005	0.007	0.408
Medium risk	0.000	0.001	0.620	0.002	0.006	0.710	-0.009	0.011	0.412
Big risk	-0.001	0.003	0.620	0.007	0.019	0.708	-0.032	0.042	0.444
Very big risk	0.003	0.005	0.619	-0.014	0.037	0.709	0.059	0.073	0.425
Perceived Risk of Burglary	(3)			(4)					
No risk	0.000	0.001	0.540	0.000	0.004	0.914	0.000	0.008	0.982
Small risk	0.000	0.001	0.540	0.001	0.004	0.914	0.000	0.008	0.982
Medium risk	-0.001	0.001	0.538	0.001	0.007	0.914	0.000	0.014	0.982
Big risk	-0.002	0.003	0.537	0.002	0.021	0.914	-0.001	0.044	0.982
Very big risk	0.003	0.005	0.537	-0.004	0.036	0.914	0.002	0.075	0.982
Panel B. Distance from the High-mast Light	**Predictor: Distance (m)**			**Mid-distance**			**Near**		
Perceived Risk of Robbery	(1)			(2)					
No risk	0.000	0.000	0.841	-0.015*	0.009	0.082	0.007	0.011	0.509
Small risk	0.000	0.000	0.841	-0.007*	0.004	0.095	0.003	0.005	0.509
Medium risk	0.000	0.000	0.841	-0.011*	0.006	0.085	0.005	0.008	0.505
Big risk	0.000	0.000	0.841	-0.037*	0.021	0.079	0.017	0.024	0.488
Very big risk	0.000	0.000	0.841	0.070*	0.039	0.076	-0.032	0.048	0.496
Perceived Risk of Burglary	(3)			(4)					
No risk	0.000	0.000	0.633	0.001	0.004	0.847	0.002	0.006	0.765
Small risk	0.000	0.000	0.633	0.001	0.004	0.847	0.002	0.005	0.765
Medium risk	0.000	0.000	0.633	0.001	0.007	0.847	0.003	0.009	0.764
Big risk	0.000	0.000	0.632	0.004	0.023	0.847	0.009	0.028	0.761
Very bgi risk	0.000	0.000	0.632	-0.008	0.039	0.847	-0.015	0.048	0.762

Note: The table reports the average marginal effects of ordinal logit regression. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 5. Marginal effects of nighttime activities on lux and distance from the nearest high-mast light

Outcome	Marg. Effect	Std. Error	p-value	Marg. Effect	Std. Error	p-value	Marg. Effect	Std. Error	p-value
Panel A. Lux Measurements	**Predictor: Avg. Path Lux**			**Lux Level 2**			**Lux Level 3**		
Use shared sanitation at night		(1)					(2)		
Yes	-0.009*	0.005	0.082	-0.050	0.038	0.193	-0.136*	0.076	0.076
Leave house at night (frequency)		(3)					(4)		
Never	-0.009*	0.005	0.090	-0.057	0.037	0.127	-0.079	0.076	0.296
1 time	0.003*	0.002	0.096	0.020	0.013	0.118	0.024	0.019	0.197
2 times	0.004*	0.002	0.093	0.024	0.016	0.134	0.035	0.035	0.325
3 times	0.001	0.001	0.101	0.009	0.006	0.149	0.014	0.015	0.360
More than 3 times	0.001	0.000	0.118	0.004	0.003	0.167	0.006	0.007	0.376
Out with friends/family at night		(5)					(6)		
Yes	-0.005	0.005	0.378	0.006	0.038	0.870	-0.050	0.077	0.518
Panel B. Distance from the High-mast Light	**Predictor: Distance (m)**			**Mid-distance**			**Near**		
Use shared sanitation at night		(1)					(2)		
Yes	-0.000	0.001	0.701	0.069*	0.042	0.098	-0.051	0.050	0.302
Leave house at night (frequency)		(3)					(4)		
Never	0.001*	0.001	0.052	-0.096**	0.040	0.018	-0.067	0.049	0.172
1 time	0.000*	0.000	0.059	0.034**	0.015	0.020	0.022	0.015	0.138
2 times	0.000*	0.000	0.054	0.040**	0.017	0.020	0.029	0.022	0.188
3 times	0.000*	0.000	0.062	0.015**	0.007	0.029	0.011	0.009	0.210
More than 3 times	0.000*	0.000	0.080	0.007**	0.003	0.046	0.005	0.004	0.228
Out with friends/family at night		(5)					(6)		
Yes	0.000	0.001	0.663	-0.065	0.041	0.115	-0.073	0.050	0.140

Note: The table reports the average marginal effects of either binary or ordinal logit regression. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 6. Regression of outcomes of interest on adjusted lux level categories

	Safe in Day	Safe at Night	Mobile	No Light	Crime Risk Index	Risk of Robbery	Risk of Burglary	Night Activity Index	Shared Sanitation Night	Leave House	Friends/ Family Out Night
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Level 2 (1 - 4.99)	-0.112	-0.051	0.043	-0.040	0.810*	-0.025	-0.068	0.056	-0.050	0.129	0.006
	(0.155)	(0.119)	(0.041)	(0.043)	(0.450)	(0.097)	(0.087)	(0.086)	(0.044)	(0.084)	(0.035)
Level 3 (5+)	0.216	0.123	0.107*	-0.014	0.177	-0.264	-0.083	0.143	-0.136	0.153	-0.047
	(0.151)	(0.127)	(0.054)	(0.055)	(0.609)	(0.162)	(0.081)	(0.255)	(0.108)	(0.198)	(0.092)
Female (=1)	-0.559***	-0.478***	-0.262***	0.065*	0.266	-0.018	-0.014	-0.168*	-0.120***	-0.187**	-0.044
	(0.119)	(0.099)	(0.040)	(0.036)	(0.310)	(0.068)	(0.064)	(0.088)	(0.036)	(0.074)	(0.031)
Age	-0.005	-0.006	-0.004***	0.002	-0.008	-0.000	0.000	-0.017***	-0.001	-0.007*	-0.006***
	(0.005)	(0.004)	(0.001)	(0.002)	(0.013)	(0.003)	(0.003)	(0.005)	(0.001)	(0.004)	(0.002)
Length of Residence	-0.014**	-0.007	-0.002	-0.001	0.027**	0.005	0.001	0.001	-0.002	0.007*	-0.001
	(0.006)	(0.005)	(0.002)	(0.002)	(0.014)	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)
Prev. Victim (=1)	-0.398***	-0.262***	-0.012	-0.035	-0.462	0.059	0.030	0.136	0.076**	0.000	0.019
	(0.115)	(0.096)	(0.040)	(0.036)	(0.377)	(0.089)	(0.061)	(0.093)	(0.037)	(0.071)	(0.043)
(Intercept)	3.509***	2.479***	0.687***	0.457***	17.142***	4.311***	4.454***	2.979***	0.616***	0.997***	0.754***
	(0.209)	(0.212)	(0.067)	(0.072)	(0.563)	(0.144)	(0.125)	(0.184)	(0.068)	(0.136)	(0.067)
Adj. R2	0.042	0.036	0.090	0.002	0.006	0.002	-0.006	0.026	0.025	0.014	0.019
Num. obs.	762	762	739	762	762	754	756	762	740	742	762
N Clusters	168	168	167	168	168	167	168	168	166	167	168

Note: Robust standard errors clustered at the path/compound level. In regressions where the lux categories are the predictors, the left out group is Lux Level 1 (0 - 0.99 lux). For both questions about perception of safety, respondents could answer on a scale from Never (1) to Always (5). For the crime risk index, values range from 1 - 25. All individual risk questions had five options ranging from 'Not a risk' (1) to 'Very big risk' (5). 'I don't know' responses were recoded as NA. For the night activity index, values range from 0 - 6. Shared sanitation at night and friends/family out at night are coded as binary, such that 1 indicates the respondent reports going outside at night for the activity and 0 otherwise. Leave house at night is coded from 0 - 4, where 0 indicates the person never left the house and 4 indicates the person left the house more than 3 times. ***p < 0.01; **p < 0.05; *p < 0.1.

ARTICLE 4: **BRINGING LIGHT TO THE DARK — CAN SOLAR PUBLIC LIGHTING IMPROVE NIGHTTIME LIFE FOR THE URBAN POOR?**

Status: Working Paper

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1. INTRODUCTION

In rapidly growing cities throughout the developing world, lack of public service provision disproportionately affects residents in poor, mostly informal neighborhoods, typically called informal settlements or "slums." Although they are home to approximately a billion urban residents (UN Habitat, 2018), i.e., about 14% of the world population, these areas are often disconnected from public urban infrastructure, such as water, sewage, electricity networks, and even more often: streetlights.

While experimental research (as well as international policy attention) has focused on access to water, sanitation, electricity, and other forms of upgrading in informal settlements (e.g., Devoto et al., 2012; Galiani et al., 2013; Gonzalez-Navarro & Quintana-Domeque, 2012; Günther & Horst, 2014), very few studies have analyzed public lighting (Gulyani & Bassett, 2007; Jaitman, 2012). One reason why there are so few studies might be that doing research in poor, informal neighborhoods at night is often difficult and requires extensive community engagement. Concerns about crime and the challenges of working in the dark likely discourage the sort of in-depth research that is afforded to other basic services in informal settlements, for which all field research can be done during daylight. Furthermore, no data exists on access to public lighting in informal settlements. While the UN Sustainable Development Goal 11 is focused on making "cities and human settlements, inclusive, safe, resilient, and sustainable," none of the targets mention access to streetlighting, despite the fact that access to public light in informal settlements falls under the purview of Goal 11 (United Nations, 2021). This omission likely also means that researchers seeking to make their research SDG-relevant do not realize that public lighting is an important avenue where research is needed.

Importantly, research from high-income countries on streetlights cannot easily be transferred to poor informal settlements. First, the density of many informal settlements makes it impossible to install standard streetlights without demolishing existing houses or taking up limited space in pathways. In addition, those living in poor informal settlements engage with public space at night in ways that are fundamentally different than those living in formal urban areas (Kamalipour, 2020). Moreover, basic services like water and sanitation are usually shared and difficult to access when it is dark (Boyce, 2019). The choice for many households is either to go outside at night to use the toilet or use a bucket inside their home, which is emptied in the morning. In addition, houses are often small and typically shared by many family members, meaning that many activities that might otherwise be done indoors happen in public areas, like laundry and food preparation. This more intensive use of public space, even to meet basic needs, set against the reality of high crime rates in many informal settlements raises questions about how public lighting can improve the quality of life at night (Matzopoulos et al., 2020; UN-Habitat, 2007, 2011).

To improve our understanding of how public light can be effectively implemented in these neighborhoods and what impact better lighting might have, we apply a cluster-randomized controlled trial to test the effectiveness of a public lighting technology developed specifically for informal settlements. To our knowledge, it is the first quantitative study to test the impact of public lighting in an informal settlement and only the second RCT studying the impact of public lighting anywhere. Studying one informal settlement in Khayelitsha, Cape Town with about 800 households, we systematically select 49 paths and randomly allocate 24 compounds to receive outdoor solar lighting mounted on each house. There are 65 paths and 26 compounds, with their respective houses, that serve as the control group.

Despite the fact that high-mast lights were already installed in this informal settlement (see Appendix D Figure 1), we find that the intervention leads to a large improvement in nighttime lux[39] levels, with a more than six-fold increase in average lux measured at the path level and a more than eight-fold increase in compounds (semi-private cul-de-sacs). This effect can be partially attributed to the fact that theft and vandalism were relatively minor. Satisfaction with the lights across both treatment groups was high and about 50% of residents say they would be willing to pay at least half the price of a replacement light. We also find that the intervention leads to a higher perception of safety among households living on lit paths, compared to those living on control paths, though we do not find any effects on safety in compounds. Greater perceptions of safety do not translate to broad-based changes in behavior. Despite reporting that they feel safer, people living in treated paths do not report that they engage in more nighttime activities overall, however, we find that both treatment and control respondents are more willing to use shared sanitation at night. In compounds, we find weak evidence that engagement in nighttime activities declined. Respondents in both paths and compounds do not report significantly fewer experiences of crime on their streets.

As the finding on shared sanitation indicates, these results require consideration of spillovers. Because anyone in the neighborhood can use a lit path even if they do not live on it, null effects could indicate that all residents are somewhat treated rather than that there is no effect. To

[39] What human perceive as brightness, is referred to as illuminance. Illuminance is defined as the amount of light falling per unit area of the surface. Illuminance can be measured in units of lux (CIE 2007).

address this, we use difference-in-differences to check for changes over time, instrumental variables to check for differences linked to non-compliance, and we analyze households separately who live adjacent to a path or compound of the opposite treatment status (varying treatment intensity), however, we do not find evidence that spillovers are large for any outcome other than the use of shared sanitation at night.

To our knowledge, no public lighting intervention in a developing country context, particularly not in informal settlements, has yet been studied using an experimental approach, therefore our study advances our understanding of the impact of public lighting in two dimensions. First, we contribute to the literature on the impact of public lighting in a new context. There is a large body of mostly observational evidence — primarily from formal cities in high-income countries — to suggest that public lighting influences and improves various aspects of nighttime life, from visibility (Boyce, 2019; Fotios, Yang, et al., 2015; Fotios & Cheal, 2009; Fotios & Uttley, 2018) to perceptions of safety and confidence at night (Atkins et al., 1991; Blöbaum & Hunecke, 2005; Boyce et al., 2000; Fotios, Yang, et al., 2015; Fotios & Uttley, 2018; Fotios & Castleton, 2016; Kaplan, 2019; Kaplan & Chalfin, 2020; Nair et al., 1997; Nasar & Bokharaei, 2017b; Nasar & Jones, 1997; Peña-García et al., 2015; Svechkina et al., 2020; Vrij & Winkel, 1991; Wu & Kim, 2018) to pedestrian activity (Fotios, Unwin, et al., 2015; Fotios & Castleton, 2016; Uttley & Fotios, 2017) to crime (Chalfin et al., 2020, 2021; Welsh & Farrington, 2008). Whereas the literature has had relatively little to say about public lighting in informal settlements (Auerbach, 2020; Gulyani & Bassett, 2007; Kretzer, 2020). We provide quantitative evidence on the impact of public lighting in a different setting — an informal settlement in a middle-income country. Although our results show that public lighting has a positive effect on perceptions of safety, similar to the literature, we find that this may not lead to widespread changes in nighttime behavior. The only other randomized controlled trial which studies the impact of public lighting focuses on public housing developments in New York City (Chalfin et al., 2021).

Second, we contribute to the nascent, but growing field of development engineering, which focuses on testing alternative approaches to technology deployment in low-income settings. By using a distributed, solar-powered public light, we test a hybrid model for what is usually a more centralized public service. In reviewing the few alternative public lighting technologies tried in informal settlements elsewhere, many embrace some form of pole-mounted lights, but imagine decentralized delivery approaches. For example, in some informal settlements in Bogotá, Colombia, residents build their own streetlights to fill gaps in light availability (Kretzer & Walczak, 2020). The NGO Liter of Light, which teaches communities to build solar-powered streetlights made from a water bottle, a solar panel, PVC pipe, and a lead acid battery, implemented these lights in an informal settlement in Chikkaballapur district, Bangalore called Kundwara (Venkat, 2016). Zonke Energy, based in Cape Town, aims to provide off-grid informal settlements with solar-powered mini-grids and affixes outdoor lights to its electricity distribution poles (Zonke

Energy, 2021).[40] Wall-mounted, outdoor solar lights, which we test in this study, represent the opposite approach. The city can still play the role of service provider, but the infrastructure is installed at the structure level to suit the urban form and to draw on local stewards — the residents themselves. Thus, we also quantitatively test a new model of public lighting delivery. This new lighting solution would also fit within the climate resilience goals of many cities to expand the use of renewable energy (e.g., City of Cape Town, 2019).[41] The dramatic decline in the cost of solar photovoltaic (PV) technology, from approximately US $2/Watt in 2010 to US $0.38 in 2019, makes a distributed solar public lighting solution not only feasible, but likely also cost effective (IRENA, 2019; Our World in Data, 2019).[42]

2. CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

Outside of poor informal settlements, there is a large body of mostly observational evidence — primarily from formal cities in high-income countries — to suggest that public lighting improves various aspects of nighttime life. Inadequate nighttime lighting hinders visibility, increasing the likelihood of tripping (Boyce, 2019; Fotios & Cheal, 2009; Fotios & Uttley, 2018) and making it hard to recognize the faces of others (Fotios, Yang, et al., 2015). A relatively large body of literature also links light levels to a perception or feeling of safety (Atkins et al., 1991; Blöbaum & Hunecke, 2005; Boyce et al., 2000; Kaplan, 2019; Kaplan & Chalfin, 2020; Nair et al., 1997; Nasar & Jones, 1997; Peña-García et al., 2015; Svechkina et al., 2020; Vrij & Winkel, 1991; Wu & Kim, 2018) and reassurance or confidence walking alone at night (Fotios, Unwin, et al., 2015; Nasar & Bokharaei, 2017a). There are also some studies on nighttime walking behavior (Fotios, Yang, et al., 2015; Fotios & Castleton, 2016; Painter, 1996; Uttley & Fotios, 2017). For example, Uttley and Fotios (2017) use pedestrian counters to study the impact of Daylight Savings Time (DST) in Virginia to show that an additional hour of ambient light in the evenings is associated with a significant 62% increase in pedestrians on the street.

Another strand of empirical literature, again mostly observational and with small sample sizes in cities in high-income countries, suggests public lighting reduces crime and fear at night (Farrington & Welsh, 2002; Welsh & Farrington, 2008). Chalfin et al. (2021) provide the first experimental evidence from a public housing development project in New York City suggesting that public lighting (in comparison to no lighting) reduces nighttime outdoor crimes by about

[40] Zonke Energy is a modular solar mini-grid company based in Cape Town, South Africa.

[41] For example, the City of Cape Town has articulated its own climate resilience strategy.

[42] In 2019, the City of Cape Town budgeted approximately US $67,000 for two high-mast lights vs. approximately US $30,000 to provide the entire informal settlement with solar public lighting. For a more detailed discussion of cost estimates see Section 3.3. Source: City of Cape Town. 2019. Almost 2500 public lights installed in Khayelitsha, work continues. Accessed Jan 27, 2021. http://www.capetown.gov.za/Media-and-news/Almost%202%20500%20public%20lights%20installed%20in%20Khayelitsha,%20work%20continues

35%.[43] Another recent study by Kaplan & Chalfin (2020) makes use of a natural experiment in Chicago – citywide public lighting outages – providing evidence that short-term outages have little impact on crimes on affected streets, but that crime in nearby streets increases alongside pedestrian activity. Moreover, Doleac and Sanders (2015) and Domínguez and Asahi (2019) both use DST in the US and Chile, respectively, to show that additional ambient light in the evenings is associated with a decrease in crime. Domínguez and Asahi (2019) also show that residential areas, which tend to have fewer streetlights, show the largest effects suggesting that more ambient light may have a larger effect in areas with less streetlighting. Kaplan (2019), however, finds the opposite, using moonlight as the exogenous light source to show that nights with brighter moonlight are associated with significantly higher crime than nights with none.

To explain how public light influences nighttime behavior, the theoretical literature broadly focuses on crime, however, two channels can also explain other aspects of nighttime life, such as access to public infrastructure, or social life after sunset, which have been so far mostly ignored. Most theory emphasizes crime because crime prevention is of critical interest to policymakers and the general public with more easily quantifiable costs to society (Chalfin, 2015) than lack of outdoor activities and increased levels of perceived safety. In addition, the theory is largely driven by empirical work in high-income countries. Although we study nighttime activity in a low-income setting, these two theories for crime in high-income settings can still usefully inform our research. The first theory, *prospect-refuge theory*, is that light directly influences nighttime outdoor activity and reduces the likelihood and fear of crime by creating opportunities for surveillance (Cozens et al., 2005; Fisher & Nasar, 1992). Under good lighting conditions, a pedestrian can more easily identify a threat and thus, feels more at ease in the space. In contrast, under poorly lit conditions, resulting shadows could give an offender the chance to watch potential victims while remaining hidden.[44] The second theory argues that it is not just illumination that influences crime and fear of crime in public space, but also the community investment that the infrastructure symbolizes (Chalfin et al., 2021; Cozens et al., 2005; Kaplan, 2019; Welsh & Farrington, 2008). Both of these theories fit within the broader theory of *Crime Prevention through Environmental Design* (CPTED), which focuses on how design interventions in the built environment can deter crime (Cozens et al., 2005). Determining which of these two channels is dominant has proven challenging, especially since they are not mutually exclusive. Researchers point to reductions in daytime crime in addition to reductions in nighttime crime, as an indicator of the community investment channel (e.g., Chalfin et al., 2021), while effects only on nighttime outcomes indicate the direct effect of illumination at night (Cozens et al., 2005; Farrington &

[43] Specifically, they study nighttime index crimes, which include: murder and non-negligent manslaughter, robbery, felony assault, burglary, grand larceny, and motor vehicle theft.

[44] It has also been argued that the opposite is possible: more light makes it easier for a potential criminal to identify a victim (Fisher & Nasar, 1992).

Welsh, 2002), but empirical studies remain inconclusive (Chalfin et al., 2021; Doleac & Sanders, 2015; Domínguez & Asahi, 2019; Kaplan, 2019; Uttley & Fotios, 2017).

From these theoretical and empirical studies, it is probable that public light also has a significant effect on perceived safety, nighttime behavior, and crime in cities of low- and middle-income countries. However, both the magnitude and the mechanism remain unclear, given that the cities in these countries are radically different than most geographies represented in previous literature. Poor informal settlements are often substantially different, both in their urban form (i.e., frequently characterized by low-rise, small, but high-density housing) as well as in their urban dynamics (i.e., people may spend more time outside). The density common to many informal settlements not only changes the dynamics of life at night, but also changes which lighting technologies are feasible. Furthermore, the need to enter public space to access basic sanitation services as well as conduct otherwise private activities, like laundry, suggest the scope for impact may differ. For example, Chalfin et al. (2021) study NYC public housing developments, which are characterized by large multi-story buildings with open public spaces where residents otherwise have private access to basic infrastructure and likely have a different relationship with public space compared to residents of informal settlements.

These contextual differences suggest that more research is needed to understand the effect of public lighting on life in informal settlements. Therefore, we not only explore whether an alternative to both high-mast lights and standard streetlights is effective in informal settlements, but also what the impact is of greater light availability on perception of safety and risk of crime, nighttime activities, and experience of crime.

3. RESEARCH DESIGN AND SETTING

3.1 STUDY SETTING

Cape Town, South Africa is home to more than 400 informal settlements and that number is always growing (Ndifuna et al., n.d.; Obose, 2021).[45] Existing policies predominantly support the continued deployment of high-mast lights for public lighting in informal settlements (City of Cape Town, 2019a; de Lille, 2012) (see Appendix D Figure 1). These are 30-40-meter-tall floodlights (also called stadium lights) that are typically installed on public land on the perimeter of informal settlements. The City of Cape Town maintains that high-mast lights are the best available solution, given the maze of property laws that affect informal settlements and the physical limitations on space. High-mast lights are also said to be more resistant to vandalism and easier to maintain in informal settlements because they can be placed in locations accessible to a service vehicle.

[45] At least 17 new informal settlements have been established in Khayelitsha, alone, since the onset of the COVID-19 pandemic in March 2020 (Obose, 2021).

On the other hand, residents of Cape Town's informal settlements, local NGOs, and our own baseline measurements (see Section 4.1 and Article 3) suggest that despite these advantages, high-mast lights do not provide bright, uniform light at night (Mtembu, 2017; Ramphele, 2017; Weyers & Notywala, 2017). In informal settlements, light from high-mast lights can create sharp contrasts and dark shadows (Kretzer, 2020). This type of lighting might not necessarily be better than none at all, since drastic changes between bright light and shadows make it even more difficult to navigate and detect potential threats (Wu & Kim, 2018). Furthermore, South Africa's electricity grid is unreliable (Kumo et al., 2021). Scheduled black-outs, called "load shedding," are common, plunging large areas of the city into complete darkness. Even when the electricity comes back, the high-mast lights are often left damaged by the outage, meaning weak or no public lighting is available until they are repaired. Finally, high-mast lights are linked to a history of racial and economic inequality in South Africa — in Cape Town, these lights are only used for residential public lighting in townships that were previously zoned as Black African under apartheid (O'Regan et al., 2014).

As in other countries, many informal settlements in South Africa are not mapped.[46] A Google Maps search will often show an empty patch of land in the shape of the informal settlement, obscuring the fact that thousands of people may live there and that an extensive pedestrian path network may exist. While it may be that informal settlements go unmapped as a result of their informality or because governments specifically do not want to acknowledge these unplanned urban neighborhoods, they also go unmapped because it is not easy to do. Houses are often built out of short-lived building materials and it is common for residents to renovate, expand, or change the orientation of their home, which can substantially alter walking paths. In addition, in South Africa's informal settlements a group of residents often decides to block a path, turning it into a compound, or cul-de-sac, to limit through traffic and enhance their sense of security. In other words, informal settlements are constantly changing, making any maps quickly outdated.

The informal settlement we selected for this study is an approximately 30-year-old, 38,200-square-meter neighborhood (Ndifuna et al., n.d.), whose path network was unmapped before we started this research. The site was selected with guidance from our local partner, a Cape Town-based NGO called the Social Justice Coalition (SJC),[47] which provided us a list of three informal settlements around Cape Town where they had contact with the leadership and that

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[46] Non-governmental organizations like Slum Dwellers International and Violence Prevention through Urban Upgrading (VPUU), and others, are working in South Africa to address the dearth of informal settlement maps. Both the Western Cape Government's Informal Settlement Support Programme, as well as the City of Cape Town have been supporting informal settlement enumerations and mapping efforts.

[47] The Social Justice Coalition (SJC) is a non-governmental organization based in Khayelitsha, Cape Town that primarily focuses on organizing legal action and grassroots activism to secure the rights of residents of informal settlements. In 2017, SJC began a campaign focused on public lighting and agreed to collaborate with us by (a) helping us identify an informal settlement and (b) providing us with Visiting Researcher status, which enabled us to make use of SJC's office space for meetings and storage. They are not directly involved in the implementation of the intervention, but rather aim to learn from the results at the end of the study.

were not included in governmental plans for upgrading in the immediate future. Along with our research partners, we ultimately selected one particular site for this study because (a) it is a manageable size to conduct a field test of a technology, (b) it is a very dense informal settlement with dark paths, making lighting particularly beneficial, and (c) it is a "contiguous" informal settlement that is not interrupted by any formal structures. Last, finding a community leadership that is willing to let a research team in without a clear promise of what the outcome of the research will be is challenging in South Africa. In this neighborhood, however, the leadership's willingness to engage in the research process enabled the field study to take shape and made data collection at night possible.

In collaboration with a research partner from architecture and local residents, we mapped and labeled the houses and the network of walkways throughout the informal settlement.[48] Based on the most up to date version of the map in August 2019, we classified the path network into three categories for the field study (Figure 1).

[48] This impact evaluation is part of a broader project, which was developed as part of the ETH Zurich Institute for Science, Technology, and Policy's Urban Research Incubator and is described in this dissertation as well as in Briers (2021). We collaborated on the coordination and implementation of the project, though we had separate research questions. For more information, see the Introduction of this dissertation.

Figure 1. Path network map of the informal settlement

Mapping done in collaboration with Stephanie Briers, Xolelwa Maha, Thabisa Mfubesi, Frans Mafilika, Noliyema Swartbooi, Tembinkosi Mositata, Thanduxolo Jubati, Pumeza Wanga, Nomsa Siyo, Yamkela Rongwana, Sibongile Mvumvu, and Jennifer Qongo.

Central streets refer to the two major arteries that bisect the informal settlement and are passable with a car or truck. They are wide enough for city service vehicles to service the waste collection point, sewerage, and toilet blocks in the neighborhood. These paths are excluded from the experiment because they are outliers in terms of length, width, and usage.[49]

Path segments are components of paths (a route to get from point A to point B). In a study of crime hot spots, Weisburd et al. (2012) define path segments by intersection and Blattman et al. (2019) draw from this, defining a path segment as the "length of street between two intersections." In defining path segments, we try to follow this approach as much as possible by adopting turning decision as our rule to define the beginning and end of a path segment. A path segment

[49] Initially, we also excluded them because we thought they would be brighter than narrower paths, however, the light measurements revealed that the lighting on these paths is not uniform (see Article 3).

begins either upon entrance from a formal street or after someone makes a decision to turn right or left from another path segment. Since informal settlements are not planned according to top-down urban planning guidelines, path segments vary in length and width.

Compounds can be thought of as cul-de-sacs within the path network. They emerge when a group of households agree to block off all other entryways to their houses except one shared entrance. That entrance is often demarcated by a gate that may or may not be locked during the day and is frequently locked at night. The space in front of the houses participating in a given compound is semi-private, as the residents typically all share it for activities like doing washing, hanging clothes to dry, preparing food, and socializing, but it is not open at all times to people who do not live in the compound.

3.2 EXPERIMENTAL DESIGN AND SAMPLE SELECTION

We use a randomized controlled trial (RCT) to study the impact of an alternative public lighting technology that is intended to provide brighter lighting on the thin pathways in informal settlements. In the case of informal settlements in Cape Town, the existing high-mast lights provide bright lighting on wider paths and to those households that live close to the high-mast lights, but they cast strong shadows in narrower paths and provide dim or no lighting in path segments and compounds that are farther away. Until now, the impact of public lighting has rarely been evaluated quantitatively in low-income settings. The randomization allows us to test both the efficacy of a new technology and service delivery option for public lighting as well as the impact of public lighting on life at night.

We chose a cluster-randomized controlled trial, randomizing at the path and compound level with the unit of observation being the household. By randomizing at the path segment and compound level, instead of at the household level, we ensure that the treatment is distributed in a way that would make logical sense to a pedestrian at night. In other words, the intervention results in lit routes, rather than randomly lit houses that might create patchy, non-uniform lighting that does not enable residents to pass from one part of the neighborhood to another on a lit route. Moreover, randomizing at the household level would have made it nearly impossible to create a viable control group, since one household could be in the control group, but live on the same path segment or compound next to several households in the treatment group, thereby experiencing almost all of the treatment effect (except direct lighting of the entryway to their house). On the other hand, clustering by area, which would have led to even fewer possible spillovers (see Section 7.2), was not possible given that the neighborhood was too small to create a sufficient number of area clusters. Including additional neighborhoods was not feasible due to the high time investment and security issues associated with working in these neighborhoods at night.

We stratify the informal settlement's path network into pedestrian path segments and compounds (see Figure 1 and Section 3.1) — on which about 800 households live. We randomized the 50 total compounds into 24 treatment and 26 control compounds using a standard randomization procedure on the computer. We used a systematic randomization approach to assign 114 path segments[50] into 49 treatment and 65 control path segments (see Figure 2 and Appendix D Figure 2). A purely random selection of path segments could easily result in a set of disparate path segments that have no practical pedestrian logic or, by chance, be clustered in one area of the settlement. Therefore, we used a systematic sampling protocol to select treatment path segments. The informal settlement we study is split by two central streets that run north-south and east-west (see Figure 1). It is also surrounded by formal, paved vehicular roads. Beginning in the northwest corner of the settlement, we selected roughly[51] every other path segment, from north to south and from west to east until the next intersection, to be a treatment path segment. At the intersection, one of the next possible segments was selected until reaching one of the central streets. When there was no intersection, the next path segment was also selected into the treatment group (see Figure 2). This approach ensures that the treatment resulted in lit paths that a person could logically walk, while avoiding giving preference to any one path into the settlement over another.

All households with a front door facing onto these treatment path segments or compounds received a free light (see Section 3.3) for the six-month study period (October 2020-March 2021), which they could keep after the study ended. Households in the control group were offered a free light at the end of the study. See Section 4.1, Table 1 for a study timeline.

The unit of analysis is the household, except for light measurements, for which we use the cluster-level average. All houses in the neighborhood — approximately 793[52] — were eligible to participate in both survey rounds, however, any household which was not randomized into an experimental group will not be included in the analysis.[53] To estimate effects, we compare outcomes in households living on treated path segments/compounds with outcomes in households on path segments/compounds that did not receive solar public lights. We are interested both in the efficacy of the solar public lighting technology and the impact of light, in general, on our outcomes of interest.

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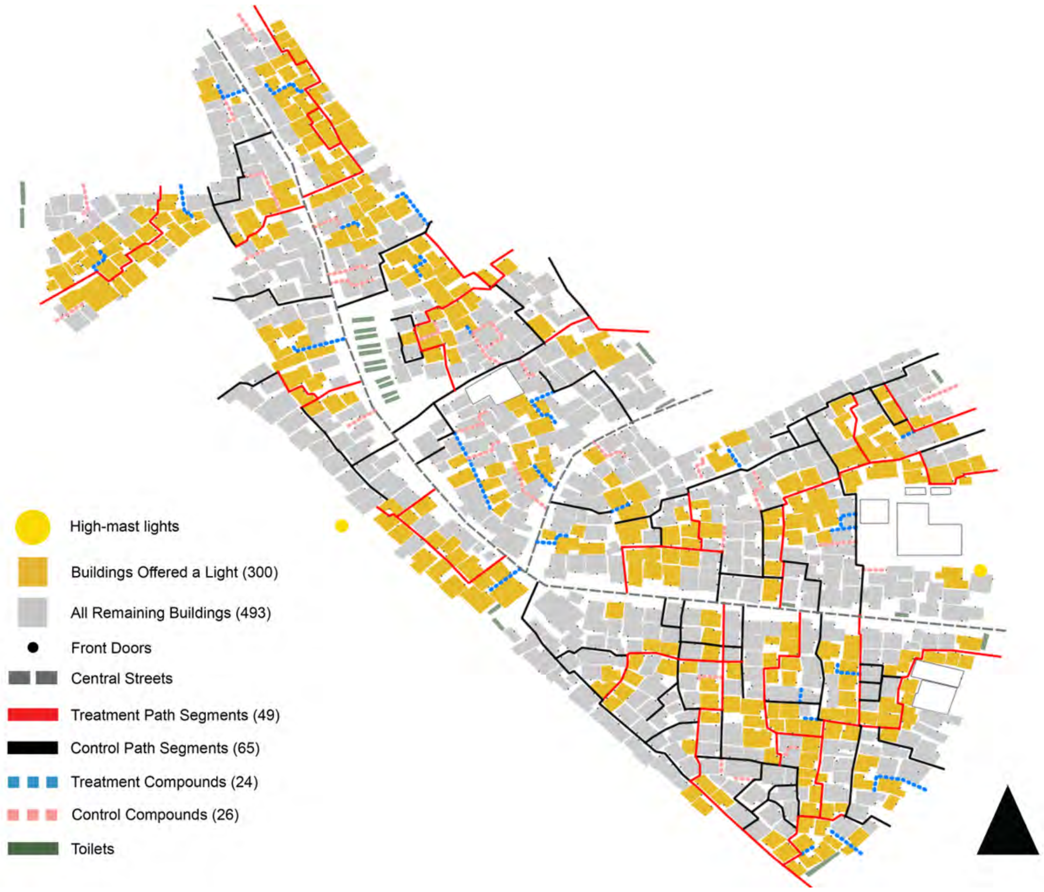
[50] Out of 133 path segments. In addition to the two central streets (see Figure 1 and Section 2.1), we exclude 17 path segments that have no front doors of houses facing them (and hence no option for a lighting intervention).

[51] We say "roughly" because there are situations where three routes all originate from the same entrance into the settlement. In cases like this, only one of the three possible routes was selected into the treatment.

[52] Based on our mapping exercise and baseline survey, we identified 793 households, but informal settlements are highly dynamic places and therefore we say approximately to account for what may be a difference in the reality today on the ground.

[53] If a household's front door did not face a path or a compound, it is not included in the experimental analysis.

Figure 2. Treatment assignment in the informal settlement



The map shows the randomization at the path segment and compound level as well as all structures that were offered a light during the implementation of the intervention.

3.3 TECHNOLOGICAL INTERVENTION

Due to the density of this informal settlement, standard pole-mounted streetlights were not a viable option. Instead, wall-mounted lights installed on the front façade of each house, usually above the front door, have the following advantages: first, they can be installed low enough that the illumination reaches the ground; second, they provide lighting in public space while also lighting the private area in front of each home; third, household members can easily keep an eye on the lights to help ensure that they are safe from theft and vandalism.[54] In addition, the advantage of a solar-powered light is that it is not vulnerable to grid reliability problems, such as planned power outages, which are common in Cape Town.

The outdoor solar light selected for this intervention is a slightly modified version of one that can be purchased "off the shelf" at many hardware stores throughout Cape Town, or anywhere

[54] The concept for wall-mounted outdoor public lighting was developed by former ETH PhD student Stephanie Briers as part of her doctoral research.

in the world (Appendix D Figure 3). The light is a 10-watt, outdoor, solar light that is equipped with a larger battery to ensure it stays illuminated during all dark hours (except, perhaps, in extreme weather conditions) and fitted with hardware that is resilient (though not impervious) to inclement weather, vandalism, and theft. The light automatically turns on at sunset and off at sunrise. It is powered by a 15-watt solar panel, with a fixed arm to secure the angle of orientation and make theft more difficult. In addition, there is a laser-printed logo and the following text "Property of Ward [Redacted]. Not for Resale" printed on the front glass. The City of Cape Town inspired the logo and text, since they also mark infrastructure that is easy to steal (e.g., water taps) to make it identifiable. The logo is also intended to signal that the light is owned and monitored by the community.

Costs for outdoor solar lights vary substantially depending on the quality of the light. These particular solar lights cost approximately US $26, including shipping from China to South Africa. In comparison, the City of Cape Town budgeted approximately US $3000 (46,192.31 ZAR) per standard streetlight in Khayelitsha in 2019/2020 and budgeted US $33,000 (32,739.56 ZAR) per high-mast light. Since standard streetlights are hardly ever used in informal settlements in Cape Town it is hard to estimate a per household cost, however, since one streetlight only provides light in a relatively small area around the light it is still clear that solar public lights are much cheaper. The two high-mast lights that provide light to this informal settlement also provide light to the areas that neighbor it, however, if we roughly calculate that these two lights serve approximately 800 households inside the informal settlement and approximately 200 less densely packed households outside, the cost is approximately US $66 per household. Since it is not clear if these budgets also account for installation and maintenance, if we add in our own installation and maintenance costs, we arrive at a cost per household of approximately US $70 for solar public lights, suggesting wall-mounted lights are cost competitive (City of Cape Town, 2019a).[55]

In September 2020, a local field team installed 281 lights above or near the front door of houses on the selected treatment path segments and compounds (see Section 3.2), such that the light beams into the public space (path or shared compound). Before installing the light, a field worker provided the household with a pamphlet containing information about the light and its purpose, then asked the homeowner for consent to install it (see Section 4.1, Table 1 for a timeline).

In addition to a distributed, solar-powered public lighting technology, we also test a hybrid public service model by hiring a local maintenance team to monitor and repair the lights. The

[55] We spent approximately US $8,000 on installation of all lights in the informal settlement and about US $2400 on maintenance during the six-month intervention. We use these numbers to arrive at the per unit cost.

approach is loosely modeled on South Africa's Expanded Public Works Programme (EPWP), which provides temporary employment to local residents to maintain public infrastructure.[56]

4. DATA

4.1 DATA COLLECTION

We collected two main types of data — a household survey (census) and lux measurements — in order to measure five main outcomes of interest: light, perception of safety, perception of crime risk, nighttime activity, and experience of crime.[57]

We surveyed one household member, preferably the household head, in each household (N = 599) in March 2019 for the baseline survey and in May/June 2021 with (N = 579) for a follow up survey after the intervention (see Section 3.3). The survey was done by field officers using tablets with questions in both English and isiXhosa, both official languages in South Africa and the two most frequently spoken languages in this neighborhood. In addition, field supervisors conducted back checks. Data was downloaded from the tablets and stored on a secure server at the end of each workday, after which the surveys were cleared from the tablets. High frequency checks were run after each day of data collection to ensure data quality.

The survey contained modules on socio-economic characteristics, housing, employment, services and infrastructure, daily activities and time use, perception of safety and risk, experience of crime, and organization capacities and political engagement. At baseline, we had three refusals and 17 empty houses, largely due to residents being away during the three-week period when we conducted the survey.

The field officers were all residents of the informal settlement, which is a common requirement for working in South African informal settlements. This approach is not without its drawbacks, particularly with respect to potential bias in survey measurements. We find this trade-off worthwhile, since it made work at night possible (one reason why so far very few quantitative studies on life at night in informal settlements exist).

An endline survey was carried out in May and June 2021, about seven months after the intervention began. Again, field officers were selected and trained, with additional training days focused on developing proficiency with reading the informal settlement map. This training enabled additional questions about where experienced crimes occurred within the informal settlement

[56] More information about the City of Cape Town's EPWP is available here: http://www.capetown.gov.za/work%20and%20business/jobs-and-skills-development/youth-careers/find-an-opportunity-with-epwp

[57] We also intended to collect pedestrian motion sensor data to measure whether lit path segments and compounds were used more frequently at night. Unfortunately, due to theft/vandalism and the unforeseen extension of the project due to the COVID-19 pandemic, we only had about 30 sensors working at endline for less than two weeks, therefore we could not collect sufficient data for the analysis.

and which areas respondents identify as dangerous. We made several changes to the questions in the endline survey, reflecting lessons learned from baseline and knowledge gained throughout the study. To better understand safety perceptions, we asked additional questions about perception of safety linked to different locations within the settlement. We also added physical attacks and vandalisms to our list of perceived risk of crime questions. Rather than asking about activities at specific locations (e.g., a specific church) we asked whether people engaged in certain activities at night (e.g., at any church). For experiences of crime, we made several changes. First, we added burglary to the list of crimes. Second, we reduced the time period we asked about from 12 months to six months. This change was necessary because we originally intended to run the intervention for 12 months, however, due to project delays, mostly caused by COVID-19, we reduced the intervention time to six months. Third, we asked respondents who experienced a robbery or physical attack to specify whether it happened during the day or at night, whether it happened inside the informal settlement or elsewhere, and, if it happened in the informal settlement, to point out on a map where the crime occurred. In addition to these changes, we also added questions about perceived quality of lighting in different areas of the neighborhood, which we did not ask at baseline to avoid priming respondents. Finally, we added a series of questions about satisfaction with the solar public lights, some of which were asked to all respondents and some of which were only asked to respondents who accepted a solar public light. For a summary of changes made to the questions that contribute to our outcomes of interest see Appendix D Table 1.

At endline, we reached a total of 579 respondents in the experimental sample. We could not reach 31 respondents that were included at baseline, but we found 13 respondents who were not available at baseline. In total, we have both a baseline and follow-up from 566 respondents. See Section 4.3 for additional details about attrition.[58]

In addition to the household surveys, we measured light brightness in lux (i.e., point horizontal illuminance) using a device called a light meter or luxmeter.[59] A team of trained residents collected lux measurements in teams of two using the light meter.[60] Again, it was necessary for residents to do this work since it would be too difficult and dangerous to send an outsider into the neighborhood at night. The teams received a detailed path network map of the informal settlement and were asked to (a) take a measurement at every front door (or gate if they could not enter a locked compound) and (b) take measurements at additional marked points on path

[58] We dropped 13 surveyors from the sample to minimize bias because they were also the only available respondent in their household and thus, responded to the survey.

[59] One lux is equal to one lumen per square meter or 0.0929 foot-candles, the American customary unit used to measure the same phenomenon.

[60] Urceri MT-912 Light Meter

segments. This procedure allows us to calculate an average lux value per path segment or per compound.

To take a measurement, the team member holding the light meter stood with their back to the front door, ensured that no roof covering was overhead, and then took a measurement while holding the light meter at the height of their belly button. To take a measurement at a marked point on a path segment, they followed the same procedure except instead of standing with their back to the door, they stood with their back to a wall on either side of the path. Since the average path width in this informal settlement is just under two meters, choosing one side of the path over the other is unlikely to have a substantial influence on the measurements.[61]

Staff recorded both the maximum and minimum lux levels at each data collection point on a paper checklist, so that the resulting data indicates the measurement point identifier (either the structure ID or the marked point ID), the date, the maximum lux measurement, the minimum lux measurement, and whether the measurement was taken at a door, a locked gate, or a marked point. It took approximately seven nights to collect a complete set of lux measurement data covering the entire informal settlement, with staff working between one to two hours per night. The team never collected data on days when load shedding (scheduled electricity outages) occurred, although it was unavoidable to collect data on days when the high-mast lights were not completely functional. A complete round of baseline lux measurements, including path points was collected in June 2020.[62]

Table 1 shows a high-level timeline of the project, including the planned and actual timing of the key activities.

[61] This approach was developed in consultation with a light engineer and verified by other light engineers.

[62] We took a first set of light measurements in February 2020, without path points, and then conducted a second baseline in June 2020. We use the measurements from June 2020 for the analysis.

Table 1. Study timeline

Activity	Planned	Actual
Baseline Household Survey	March 2019	March 2019
Baseline Sensor Measurement	Oct.-Dec. 2019	Oct.-Dec. 2019
Baseline Lux Measurement	February 2020	Feb. & June 2020
Intervention Start	March 2020	**October 2020**
Endline Lux Measurement	February 2021	**Mar./April 2021**
Endline Household Survey	March 2021	**May/June 2021**
Second Phase Light Installation	April 2021	**Aug./Sep. 2021**

A study timeline showing the planned and actual timing of major activities because of COVID-19.

4.2 BALANCE AND STATISTICAL POWER

Baseline data collection was used to better understand the existing lighting situation in the informal settlement and how people feel and act in public space at night (Table 2). The lighting levels in this informal settlement before the intervention in September 2020 were low. The average measured lux level was low at 2.6 lux for paths and 1.5 lux for compounds. These averages are lower than the minimum average requirement for wholly pedestrian streets in the city center according to City of Cape Town guidelines (Sustainable Energy Africa, 2012).[63] Based on conversations with local lighting professionals including those in the City of Cape Town's Public Lighting Development department, the minimum value for any single measurement on a pedestrian path should be 1 lux: we have 587 (66%) spot lux measurements below 1 lux (N = 889, including path points).[64]

The baseline survey also provided us with a better understanding of the basic characteristics of the neighborhood, what residents do after sunset, and how safe they feel. In March 2019, the settlement had about 2,280 residents living in 793 residential structures, each with an average of 2.5 rooms and an average household size of about three people. About 22% of respondents reported living on a household income of 400 ZAR/US $26 or less per month (though many also receive grants through South Africa's social safety net), while the median income range is between 1500 – 3500 ZAR/US $97 - 225.[65] About 70% of residents have completed at least Grade 10 (half of high school, mandatory in South Africa). Almost every resident relied on shared public toilets, though some residents report that they have family living in the formal area nearby

[63] Note that there are no specific regulations for informal areas.

[64] Due to the quality of our device, we probably measure more zeroes when the lux level is below 1 lux than a professional lighting engineer with a much more expensive device might, who might measure more values between 0 and 1.

[65] Currency conversions were done on Nov. 17, 2021 when USD $1 = 0.064 ZAR and values are rounded to the nearest US dollar.

and go there to use a private toilet. During the baseline survey period, sunset was between 7:00-7:30 pm and sunrise at 6:30-7:00 am. Fewer than half of respondents said they went outside at night to use the public toilets, many report that they use a bucket inside their house at night or avoid the toilet altogether. About 50% of respondents report that they did not leave their house after 8:00 pm the night before. In comparison, only 6% say they never left the house during the daytime the day before. Approximately 75% of respondents report going to sleep between 8:00 pm and 11:00 pm, while about 51% report waking up between 5:00 am and 8:00 am. These times indicate that there is need for public lighting very early in the morning and until quite late at night, at least for visibility.

When it comes to safety, 55% of respondents report that they do not feel safe in the informal settlement during the day and about 80% report that they do not feel safe at night, thus nighttime is associated with higher levels of fear. In addition, about 25% of respondents report that they or someone in their household had been robbed, 16% report that their house was vandalized, and 11% report that they or someone in their household was physically attacked in the previous 12 months, indicating both a lack of perceived and actual safety.

As explained in Section 3.2, we stratified the path network into path segment and compound clusters and randomized at this level (see Appendix D Figure 2). On average, there are 3.75 households on each of the 114 path segments and 50 compounds in this study. Based on a *t*-test of means, the random assignment of the lighting intervention led to treatment and control paths and compounds that are not significantly different from each other (see Table 2).

Table 2. Balance at baseline

	Paths					Compounds				
Variable	**Obs**	**Mean**	**Control**	**Treat**	**p-value**	**Obs**	**Mean**	**Control**	**Treat**	**p-value**
Panel A										
Female	442	0.55	0.56	0.54	0.71	157	0.62	0.64	0.61	0.67
Age	442	38.82	38.40	39.39	0.38	157	39.28	39.31	39.25	0.97
Attained education level[a]	440	5.40	5.45	5.32	0.47	156	5.42	5.48	5.35	0.65
Monthly Income[b]	414	3.16	2.99	2.71	0.06	145	3.26	3.18	3.34	0.59
Household members	442	3.03	2.94	3.16	0.23	157	2.99	2.91	3.06	0.60
Rooms in house	442	2.52	2.54	2.49	0.60	157	2.31	2.29	2.33	0.82
Length of residence	441	16.57	16.35	16.86	0.63	157	17.80	18.26	17.35	0.63
Risk Index (max: 15)	442	10.92	11.17	10.59	0.03	157	10.91	11.08	10.75	0.43
Panel B										
Avg. lux (path-level)	112	2.57	2.33	2.87	0.27	50	1.52	1.70	1.35	0.41
Safety Perception Index (max: 5)	442	1.25	1.22	1.29	0.40	157	1.15	1.23	1.08	0.29
Feels safe in this informal settlement during day	442	0.47	0.45	0.49	0.45	157	0.44	0.50	0.38	0.13
Feels safe in this informal settlement at night	442	0.22	0.23	0.21	0.73	157	0.20	0.26	0.15	0.11
Carries no private light outside at night	442	0.56	0.54	0.59	0.28	157	0.51	0.47	0.54	0.38
Night Activities Index (max: 8)	442	3.36	3.40	3.32	0.59	157	3.25	3.19	3.30	0.63
Time wake up	440	7.14	7.28	6.96	0.09	157	7.29	7.43	7.15	0.44
Time go to sleep	434	19.99	20.00	19.98	0.96	157	19.82	20.21	19.46	0.29
Go outside to use toilet at night	429	0.49	0.52	0.44	0.09	153	0.40	0.41	0.39	0.79
Out with friends/family at night	442	0.49	0.51	0.46	0.34	150	0.46	0.49	0.43	0.48
Leave house at night	435	0.50	0.47	0.54	0.14	150	0.42	0.41	0.43	0.81
Time kids come in at night	250	19.23	19.38	19.07	0.05	157	19.49	19.64	19.35	0.35
Time women come in at night	314	19.71	19.88	19.50	0.13	152	19.72	20.07	19.42	0.11
Time men come in at night	302	20.71	20.81	20.58	0.32	90	20.57	20.97	20.27	0.09
Exp. of Crime Index (max: 3)	442	0.53	0.55	0.50	0.58	157	0.47	0.59	0.34	0.04
Someone in household robbed in last 12 months	435	0.26	0.29	0.23	0.17	156	0.22	0.29	0.16	0.07
Someone in hh physically attacked in last 12 mon.	438	0.11	0.12	0.10	0.44	157	0.11	0.13	0.09	0.43
House vandalized in last 12 months	435	0.16	0.14	0.18	0.29	156	0.14	0.18	0.09	0.09
Risk of Crime Variables										
Risk of robbery (max: 5)	435	4.27	4.32	4.21	0.34	156	4.49	4.50	4.47	0.86
Risk of burglary (max: 5)	438	4.41	4.41	4.42	0.85	155	4.56	4.67	4.45	0.10

Notes: The table reports a t-test of means for respondent characteristics in Panel A and for the outcomes of interest measured at baseline in Panel B. The sample includes all respondents at baseline assigned to an experimental group. [a]For attained education level, the mean is consistent with an educational attainment between Grade 10 and 11. [b]For monthly income, the mean is associated with a range between 801 - 1,500 ZAR. For all risk questions, respondents could choose a response from a from a six-point scale, with 0 indicating no risk and 5 indicating a very big risk (and not applicable). The Risk Index is a count index measuring perception of risk in the next 12 months. Inputs include: risk of injury from a taxi or vehicle, risk of gender-based violence, risk of a house fire. The risk of crime variables are not grouped into a count index.

Based on these baseline survey measurements, we estimate with a power of 0.8 and statistical significance of alpha 0.05 that we are powered to detect an effect on average lux, our primary indicator of efficacy, of 1.96 lux from a baseline mean of 2.29 lux. In addition, we are powered to detect an effect of 0.33 on the safety perception index from a baseline of 1.22, an effect of 0.48 on the night activity index from a baseline of 3.33, and an effect of 0.31 on the experience of crime index from a baseline of 0.51 (Table 3).[66]

Table 3. Power calculations

Outcome	Type	MDE P < 0.05	MDE in Std. Devs	MDE P < 0.01	Mean	Std. Dev.	Min/Max	ICC
1. Average Lux (path level)	continuous	1.96	0.44	2.40	2.29	4.43	0/25	N/A
				Indices/*Individual Outcomes*				
2. Perceived Safety Index	ordinal	0.33	0.36	0.41	1.22	0.92	0/3	0.048
Ex. Feel Safe in PJS at Night	binary	0.33	0.80	0.36	0.22	0.41	0/1	0.042
3. Night Activity Index	ordinal	0.48	0.34	0.59	3.33	1.42	0/8	0.000
Ex. Use Shared Toilet at Night	binary	0.62	1.24	0.65	0.47	0.50	0/1	0.114
4. Experience of Crime Index	ordinal	0.31	0.39	0.38	0.51	0.80	0/3	0.112
Ex. Experience Vandalism in Previous Yea	binary	0.27	0.75	0.31	0.15	0.36	0/1	0.079

All calculations assume a desired power of 80%, a two-tailed test, an average of 3.75 houses per path segment/compound, and 73 clusters (path segments and compounds) in the treatment group. For each index, we also report a power calculation for one example input variable. Note that since the study was pre-registered, we made the following changes. The perceived safety index no longer contains two input variables it previously included. In addition, the experience of crime index and the input crime variables were reverse coded, such that no experience of crime was equal to 1 and an experience of crime was equal to zero. Since this caused confusion, we now code the variables as equal to one if a crime was experienced and zero if not.

4.3 ATTRITION

At endline, we experienced some attrition. Given the amount of resident turnover that is common in informal settlements this was expected. If the same family lived in the same house as at baseline, we interviewed the same person. In the event of death or if the previous respondent moved away, we spoke to the new household head. If a new family moved into the structure, we interviewed the new household head. A household-level observation dropped out of the sample if the house was demolished, is empty, or the household head declined to be surveyed.

Of the initial 599 structures in our baseline sample, one was demolished at endline, for 73 structures (12%) a new family moved in, for 64 structures (10.6%) we only could interview another member of the same family as the baseline respondent, and for 435 structures (72.6%) we interviewed the same person as at baseline. In addition, we interviewed 13 respondents at endline whose houses were empty at baseline. For the final analysis, we did not exclude structures where

[66] The study pre-registration can be found here: Borofsky, Yael and Isabel Günther. 2020. "New Public Lighting in Informal Settlements: A Field Experiment in Cape Town, South Africa." AEA RCT Registry. December 15. https://doi.org/10.1257/rct.3777-1.0

a new family moved in, so in total the attrition from baseline to endline is only 5% and we re-interviewed 95% of houses. Since we randomized at the path segment or compound level, this attrition affects our household sample and thus cluster size, but it also affected path-level sample size on two path segments, leaving us with a final sample of 112 path segments and 50 compounds.[67] To be sure that moving house was not correlated with treatment status, we test for differences between treatment groups for those who moved. Between the end of baseline and start of endline, 10% of the treatment group and 11% of the control group moved out of their home — this difference is not significant.

In April 2021, the field team collected a final round of lux measurements. For these measurements, attrition only occurs if a house no longer exists.

5. EMPIRICAL FRAMEWORK

5.1 HYPOTHESES

Based on the discussion in the existing literature about how light can affect life at night, we focus on measuring the impact of randomly assigned solar public lights on five broad outcomes of interest: light levels (avg. lux/path or compound), perception of safety, perceived risk of crime, nighttime activity, and experiences of crime.

Linked to these outcomes are the following five research questions and null hypotheses, H_0, that we expect to reject with our data.

1) The first-order question is whether wall-mounted, outdoor solar public lights provide effective public lighting. ***A1.H₀:*** *Path segments/compounds that receive the lighting intervention demonstrate no difference in measured brightness (lux) from areas that do not receive the lighting intervention.* We measure efficacy as average lux per path segment/compound. Additionally, we compare lux measurements to three variables indicating respondent perception of brightness at their front door, in their path, and in the informal settlement, overall.

2) The literature on public lighting for high-income countries indicates that people perceive an area to be safer if it is better lit. Therefore, we test whether respondents living in lit areas report feeling safer in the informal settlement, both during the night and the day. ***B1.H_0:*** *Residents living on path segments/compounds that receive the lighting intervention do not report any difference in feelings of safety as compared to residents living in areas that do not receive the lighting intervention.* We measure perceptions of safety using self-report survey questions focused on safety during the day and night in the informal settlement overall, in the path where they live, and inside their house. In addition, we include questions

[67] This situation is possible since some paths have very few households on them, so attrition can mean that we lose household representation for a given path at endline.

asking about perceptions of safety walking to do different activities and whether they carry a private source of light (e.g., cell phone light) when going out at night. Using these responses, we create a count index where the higher the value, the safer the respondent reports feeling. We also analyze perception of safety in the informal settlement, in the path, and inside the house during the day and night individually. By comparing the difference between reported daytime and nighttime safety survey responses, we also test the theory (see Section 2) that the infrastructure itself, rather than just the light, influences feelings of safety.

The literature is inconclusive about whether light affects perceived risk of crime (Atkins et al., 1991), therefore we test whether respondents living in lit areas report a lower perceived risk of certain crimes. ***B2.H₀:*** *Residents living on path segments/compounds that receive the lighting intervention do not report any difference in perception of risk of crime as compared to residents living in areas that do not receive the lighting intervention.* We ask respondents about their perceived risk of certain crimes happening to them or someone in their family in the next 12 months. We focus on burglary and vandalism since these are crimes that directly occur in the path segments/compounds we study.

3) We expect individuals living on lit path segments/compounds to report engaging in more activities outside at night. ***C1.H₀:*** *Residents living on path segments/compounds that receive the lighting intervention do not report a higher engagement in nighttime outdoor activities compared to residents living in areas that do not receive the lighting intervention. Moreover, residents in treatment areas do not go inside for the night or to bed later than residents in control areas.* We measure reported nighttime activities using self-reported survey responses to the following questions: time wake up, time go to sleep, use of shared sanitation facilities, go to Spaza shop at night,[68] go to church at night, do laundry outside at night, spend time with friends/family outside, spend time with friends/family in front the house, whether respondents report leaving the house at night, time men, women, and children come in for the night, and activity diary questions between 6:00 – 9:00 pm and between 5:00 – 8:00 am. We use these variables to create a count index to measure willingness to engage in activities in public space at night, where higher values indicate more activities or time in public space at night. We also separately analyze use of shared sanitation facilities, spending time with friends/family outside, spending time with friends/family in front of the house, and whether the respondent reports leaving the house at night at all.

4) Due to the relatively small sample size and the limitations of police-reported crime incidence (e.g., underreporting), we do not analyze the effect of public light on crime incidence, but rather on self-reported experiences of specific outdoor crimes in the preceding six months. ***D1.H₀:*** *Residents living in areas that receive the lighting intervention do not*

[68] A Spaza shop is a convenience store.

report any difference in experience of crime in the previous six months as compared to residents living in areas that do not receive the lighting intervention. We ask about robbery, physical attack (outside), vandalism, and burglary. For robbery and physical attacks that happened within the informal settlement, we asked whether they occurred during the day or night and asked respondents to point on the map where the crime occurred. This information allows us to create a measure of day crimes and night crimes at the path level, which we can also compare to try to understand whether the community investment mechanism dominates. We also create a count index to develop an overall measure of the burden of experienced crime for residents, where higher values indicate more experienced crimes. Finally, we analyze burglaries and vandalism individually since these crimes occur directly on the path segments/compounds we study.

Appendix D Table 1 reports the variables that make up each count index and shows the differences in the indices between baseline and endline.

5.2 TREATMENT EFFECTS

We will estimate the intention to treat (ITT) effect of the public lighting intervention, as well as the effect of lighting by applying two approaches. First, to test the impact of the light intervention (ITT) on the various outcomes, we will estimate equation (1):

$$OUTCOME_{ip} = \beta_0 + \beta_1 TREAT_p + \Theta X'_{ip} + \epsilon_{ip} \quad (1)$$

where $OUTCOME_{ip}$ is the endline outcome value measured for household i living on the path segment or compound p; $TREAT_p$ is an indicator for a path segment or compound assigned to the public lighting intervention (and zero otherwise); X'_{ip} is a vector of baseline covariates; and ϵ_{ip} is the standard error clustered at the level of randomization (path segment/compound).

For outcome variables for which we have baseline data (see Section 4.1 for a discussion of changes in questionnaire between baseline and endline), we will also estimate a difference-in-difference model (2):

$$OUTCOME_{ip} = \beta_0 + \beta_1 TREAT_p + \beta_2 ENDLINE_{ip} + \beta_3 (TREAT * ENDLINE)_{ip} + \Theta X'_{ip} + \epsilon_{ip} \quad (2)$$

Where $ENDLINE_{ip}$ is a dummy equal to 1 for the endline survey and 0 for the baseline survey; and β_3 is the difference-in-difference estimator.

Actual light intensity by the solar lights can vary due to the number of front doors in a particular path segment/compound, the variance of light created by the combination of the solar lights and the pre-existing high-mast lights, and, in rare incidences, non-compliance and light malfunctioning. To check for robustness to treatment non-compliance, we apply an instrumental variables (IV) approach, where our treatment dummy is the exogenous instrument that alters brightness levels (measured in lux):

$$D_p = \alpha_0 + \alpha_1 TREAT_p + \Theta X'_{ip} + \epsilon_{1ip} \qquad \text{first stage} \qquad (3)$$

$$OUTCOME_{ip} = \beta_0 + \beta_1 \widehat{D_p} + \Theta X'_{ip} + \epsilon_{2ip} \qquad \text{LATE} \qquad (4)$$

In equation (3), $TREAT_p$ is the instrument that equals 1 for path segments and compounds p assigned to the treatment group and 0 otherwise. D_{ip} is the light treatment intensity, which is the average lux on each path segment or compound p. In equation (4), $OUTCOME_{ip}$ is any of the mentioned outcomes of interest in Section 5.1 (except average lux). β_1 captures the Local Average Treatment Effect (LATE), which is the effect of having more light (measured as average lux) on the outcomes of interest. $\Theta X'_{ip}$ are additional control variables as measured at baseline. Finally, we also check for spillovers by estimating the treatment intensity for households living on the border of a path segment or compound of the opposite treatment status (see Section 7.2).

We recode all individual outcomes (non-index outcomes) as binary variables to make interpretation easier, since the results are very similar when individual outcomes that were originally ordinal are not recoded.

5.3 HETEROGENEOUS EFFECTS

We will analyze the effect of the new lights by proximity to the nearest high-mast light, for two reasons. First, the high-mast lights are likely to have an influence on brightness, however, the literature suggests that beyond a certain threshold there are diminishing returns to additional brightness (Boyce et al., 2000; Fotios & Castleton, 2016; Svechkina et al., 2020). Second, many households are rather far from both high-mast lights, and as a result, also far from what could be considered the center of gravity of the settlement, where the main Spaza shop is, the largest collection of toilets, etc. Therefore, we test to see how the dynamics captured by distance to the nearest high-mast light influences the impact of the treatment. In addition, we will analyze effects separately by gender, since gender is discussed in the literature as a key predictor of reassurance or confidence in public space at night and fear of crime (e.g., Blöbaum and Hunecke, 2005; Boomsma and Steg, 2014; Roman and Chalfin, 2008). Due to the discussion of gender effects in the literature, we will study it even though our survey targets household heads and we do not representatively sample for gender.

5.4 MULTIPLE HYPOTHESIS TESTING

We test the impact of the treatment on a total of 34 outcomes. Of these, six are indices (see Appendix D Table 1 for the variables constituting the indices). Aggregation using count indices mitigates some of the risks associated with multiple outcome and hypothesis testing, but not all of them, since we also look at several variables individually. Therefore, we use a Bonferroni correction to account for multiple hypothesis testing. We report all the main results with the adjusted p-values in Appendix D Table 2.

6. RESULTS

6.1 SOLAR PUBLIC LIGHTING INCREASES LIGHT LEVELS AT NIGHT

The first objective is to determine the extent to which the intervention improved lighting levels in the informal settlement. We estimate equation (1) and (2) in Table 4 on measured average lux and equation (1) on self-reported measures of brightness in front of the respondent's house, in the path where the respondent lives, and in the informal settlement, in general.[69]

The results in Table 4 show that the lights increase average lux by about 12.5 lux in paths and 16 lux in compounds or a six-fold increase in brightness on paths and an eight-fold increase in brightness in compounds. Since the front doors typically all face each other in compounds, the lights all shine into the center, making compounds likely to be brighter than paths. For comparison, the minimum average lux requirement for wholly pedestrian streets in the city center is 10 lux. The solar public lighting exceeds this requirement (Sustainable Energy Africa, 2012). It is important to note that we find these large effects despite the fact that lights which were stolen (N = 6) or vandalized (N = 7) during the intervention were not replaced. Columns 3-5 (paths) and 8-10 (compounds) report the effect of treatment assignment on self-reported perceptions of brightness. We find that among respondents in paths, 69% more report that the front door is well lit, 68% more report that where they live is well lit, and 15% more report the informal settlement is well lit. The size of the effect decreases as the location of interest broadens, which is expected since roughly two-thirds of the informal settlement did not receive solar public lighting. In compounds, there is no effect of treatment on the perception that the informal settlement, overall, is well lit — a minority, roughly 35% of each group, agrees it is. Meanwhile, 75% more report the area in front of their house is well lit and 57% more report the path where they live is well lit. Since we asked about the path, even to residents who live in compounds, it is likely they considered the path they use to access the compound where they live, which may or may not be treated. We re-estimate the models with binary outcomes using binary logistic regression and find very similar results. The average marginal effects are reported in Appendix D Table 3.

[69] We do not estimate a difference-in-difference model (equation 2) because we did not ask these questions at baseline.

Table 4. Effect of treatment on brightness

	Path					Compound				
	Endline Avg. Lux		Front of House	Path	Informal Settlement	Endline Avg. Lux		Front of House	Path	Informal Settlement
	OLS	DiD	OLS	OLS	OLS	OLS	DiD	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat (=1)	12.525***	0.499	0.694***	0.675***	0.145***	16.045***	-0.381	0.753***	0.572***	-0.013
	(1.828)	(1.111)	(0.039)	(0.042)	(0.048)	(1.672)	(0.813)	(0.061)	(0.072)	(0.081)
Endline (=1)		0.002					0.308			
		(0.950)					(0.817)			
Treat*Endline		11.874***					16.546***			
		(1.633)					(1.801)			
(Intercept)	2.354*	2.402***	0.217***	0.139***	0.242***	1.968**	1.675***	0.195***	0.222***	0.351***
	(1.347)	(0.677)	(0.033)	(0.027)	(0.032)	(0.781)	(0.589)	(0.054)	(0.063)	(0.053)
Adj. R^2	0.377	0.363	0.471	0.454	0.022	0.628	0.690	0.576	0.323	-0.006
Num. obs.	425	830	425	402	425	154	302	154	145	154
Clusters	112	112	112	112	112	50	50	50	49	50

Note: Standard errors clustered at the level of randomization. All three self-report variables are constructed as binary outcomes from variables in which respondents could answer, 'Totally dark' = 0, 'Somewhat dark' = 0, 'Not much light, but not dark' = 0, 'Somewhat lit' = 1, 'Very well lit' = 1. ***p < 0.01; **p < 0.05; *p < 0.1.

6.2 SOLAR PUBLIC LIGHTING INCREASES PERCEPTIONS OF SAFETY AT NIGHT

Table 5 (Panel A) reports the effect of treatment on perceived safety, both at night and during the day. Column 1 reports the effect of treatment on the extended perceived safety index for which we only have an endline measure (11 input variables). Treatment is associated with a significant 19% percentage point change ($p < 0.05$) in overall perception of safety (from an index of 3.45 out of 11 in the control to 4.11 in the treatment group). In column 2, when we use the shorter version of the perceived safety index as the outcome (3 input variables), we find a similar effect, however, the difference-in-difference estimator is not significant (column 3).

Columns 4-11 focus on perception of safety in three locations, all of which are inputs to the extended safety index. These measures allow us to compare daytime and nighttime perceptions of safety: in the informal settlement (columns 4-7), in the respondent's own path (columns 8-9), and inside the respondent's house (10-11). We find that the treatment is linked to a significant 10 percentage point increase (from 41% feeling safe during the day) in the share of respondents reporting they feel safe in the informal settlement during the day and a 6 percentage point increase (from 12.7% feeling safe during the night) at night: an almost 50% increase in perceived safety at night. Using the difference-in-difference model (columns 5 and 7), the coefficients are similar, but not statistically significant. We also see that overall perception of safety at night has decreased between baseline and endline. The reason is probably linked to an increase in gang-related crime in the neighborhood, particularly greater demands for protection money. In the path where the respondent lives, there is no effect of the treatment on daytime perception of safety, but there is a significant 10.7 percentage point increase (a doubling) in perception of safety in the path at night. We do not find that treatment has any effect on respondents' perception of safety inside their homes. In compounds, we find no effect of treatment status on any outcome (Table 5, Panel B).

In addition to perception of safety, we also test whether the treatment influences respondents' perceived risk of crime. In paths (Panel A), we find that the treatment is associated with a 4 percentage point decrease in perceived risk of burglary (column 12), however, when we control for differences at baseline, the difference-in-difference estimator is not significant (column 13). We do not find an effect of treatment on perceived risk of vandalism. In compounds (Panel B), we find no effect on either measure of perceived crime risk.

Finally, we also asked respondents who accepted a light some questions about their experience with the light. Almost every respondent agreed the light made the area in front of their house bright, it made them feel safer opening the front door at night, and safer in the area outside their house. These opinions are consistent with our findings that the treatment influences perception of safety, particularly at night.

We re-estimate all models with binary outcomes in Table 5 using binary logistic regression and find very similar results. We report the marginal effects in Appendix D Table 4.

Table 5. Impact of treatment on perceptions of safety

	Safety Index			Inf. Sett. Day		Inf. Sett. Night		Own Path Day	Own Path Night	In Home Day	In Home Night	Perceived Burglary Risk		Perceived Vandalism Risk
	OLS	OLS (Short)	DiD (Short)	OLS	DiD	OLS	DiD	OLS	OLS	OLS	OLS	OLS	DiD	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A - Paths														
Treat (=1)	0.660**	0.210**	0.062	0.105**	0.037	0.061*	-0.012	0.085	0.107***	0.038	0.071	-0.044**	-0.007	0.003
	(0.286)	(0.086)	(0.104)	(0.047)	(0.050)	(0.034)	(0.048)	(0.054)	(0.034)	(0.042)	(0.054)	(0.020)	(0.023)	(0.035)
Endline (=1)			-0.140*		-0.047		-0.102***						0.043**	
			(0.081)		(0.040)		(0.037)						(0.020)	
Treat*Endline			0.157		0.075		0.068						-0.038	
			(0.127)		(0.064)		(0.056)						(0.030)	
(Intercept)	3.451***	1.111***	1.229***	0.414***	0.449***	0.127***	0.225***	0.467***	0.102***	0.730***	0.443***	0.984***	0.940***	0.918***
	(0.140)	(0.049)	(0.069)	(0.029)	(0.031)	(0.019)	(0.030)	(0.035)	(0.018)	(0.028)	(0.031)	(0.010)	(0.016)	(0.020)
Adj. R^2	0.014	0.011	0.006	0.009	0.003	0.005	0.008	0.005	0.020	0.000	0.003	0.012	0.006	-0.002
Num. obs.	425	425	830	425	830	425	830	425	425	425	425	425	826	422
Clusters	112	112	112	112	112	112	112	112	112	112	112	112	112	112
Panel B - Compounds														
Treat (=1)	-0.013	-0.182	-0.157	-0.104	-0.114	-0.091	-0.090	0.000	0.026	0.013	0.104	0.000	-0.042	0.024
	(0.497)	(0.145)	(0.156)	(0.087)	(0.078)	(0.060)	(0.061)	(0.097)	(0.073)	(0.085)	(0.088)	(0.045)	(0.027)	(0.044)
Endline (=1)			0.105		0.013		-0.026						-0.053	
			(0.174)		(0.093)		(0.065)						(0.035)	
Treat*Endline			-0.025		0.027		0.000						0.041	
			(0.242)		(0.134)		(0.079)						(0.055)	
(Intercept)	3.688***	1.312***	1.211***	0.506***	0.487***	0.208***	0.237***	0.506***	0.169***	0.727***	0.390***	0.935***	0.987***	0.896***
	(0.413)	(0.103)	(0.113)	(0.055)	(0.065)	(0.049)	(0.051)	(0.076)	(0.057)	(0.064)	(0.066)	(0.031)	(0.013)	(0.034)
Adj. R^2	-0.007	0.004	0.001	0.004	0.001	0.009	0.005	-0.007	-0.005	-0.006	0.004	-0.007	0.000	-0.005
Num. obs.	154	154	302	154	302	154	302	154	154	154	154	154	300	152
Clusters	50	50	50	50	50	50	50	50	50	50	50	50	50	50

Note: Standard errors clustered at the level of randomization. The extended version of the perceived safety index (only endline) contains 11 binary input variables, which include: perception of safety in the informal settlement during the day, perception of safety in the informal settlement at night, perception in the path where you live during the day, perception of safety in the path where you live at night, perception of safety inside your house during the day, perception of safety inside your house at night, feel safe walking to the spaza shop at night, feel safe walking to the toilet at night, feel safe walking to visit friend/family in the informal settlement at night, carries no private light when walking outside at night. The short version of the perceived safety index for which we also have a baseline measure contains 3 binary input variables, which include: perception of safety in the informal settlement during the day, perception of safety in the informal settlement at night, carries no private light when walking outside at night. The outcome variables for columns 4-11 are binary indicator of perception of safety in the informal settlement during the day/night, perception of safety in the path where you live during day/night, and perception of safety inside your house during day/night, where 'Never' and 'Rarely' are coded as 0 and 'Always', 'Most of the time' and 'About half the time' are coded as 1. The outcome variables for columns 12-14 are binary indicators of perceived risk of burglary and vandalism coded such that 'Not a risk' = 0, 'Small risk' = 0, 'Medium risk' = 1, 'Big risk' = 1, and 'Very big risk' = 1. There is no difference-in-difference estimation for perceived vandalism risk because we did not ask that question at baseline. ***p < 0.01; **p < 0.05; *p < 0.1.

6.3 SOLAR PUBLIC LIGHTING HAS NO EFFECT ON OVERALL NIGHTTIME ACTIVITY

Table 6 reports the impact of treatment assignment on both the extended nighttime activity index (18 variables), the short nighttime activity index (8 variables), and three input measures of nighttime activity for which we also have baseline data (whether respondents use shared sanitation at night, go out with family/friends at night, leave the house at night for any reason). In addition, we test the local effect of the light by estimating the effect on whether respondents report spending more time in front of their house at night with family and friends. As a comparative exercise, we also report effects on two outcomes in which respondents were asked to state how much they agree with two statements: 1) *A well-lit area in front of my home makes me more likely to leave my house at night*.; 2) *I am more likely to go somewhere in [the informal settlement] at night if I know the way to go there is well lit.* In other words, we also test how much people *think* they will go out at night if the area is well lit (expectation) in addition to how much they actually report going out at night.[70]

In general, we do not find that people spend more time outside when treated with lights – neither for lit paths nor for lit compounds (Columns 1-10), regardless of whether we use the extended or short nighttime activity index or any other nighttime activity variable. In treated compounds, households even seem to spend less time outside (when considering the nighttime activity index).

We do, however, find that over time (between baseline and endline) households are less likely to go outside, as indicated by the endline dummy in the difference-in-difference specification (Panel A, column 3). The lack of a treatment effect in paths is unlikely to be explained by spillover effects from treatment to control paths. If the treatment led to a substantial increase in households going out in both the treatment and control groups (i.e., with spillover effects), we would expect a positive time coefficient. Of course, without a counterfactual over time it might also be that without the intervention both control and treatment groups would go out even less, but at least the positive effect does not seem to be strong. Moreover, for feelings of safety we find a clear difference between the treatment and control groups – further indicating that spillovers cannot explain all of the missing effect on nighttime behavior.

We suspect that nighttime activity went down over time partly due to the COVID-19 pandemic and also partly due to the rise in gang activity, which is also reflected in the general decrease in perception of safety at night (see Table 5, column 7).

In both paths and compounds, however, we find that respondents are significantly more likely to report using shared sanitation at night at endline compared to baseline (column 5, both panels). This is the one outcome for which we find some evidence of spillover, as these effects indicate that respondents in both treatment groups are impacted. Given that access to sanitation is a basic need (different from social activities outside at night), it might be that more light

[70] We only asked these questions at endline.

availability, even if it is not directly where the respondent lives, prompts respondents from both the treatment and the control group to stop using a bucket at night, which people find highly shameful, and use shared sanitation facilities instead. Again, we cannot rule out that some other factor explains the behavior change. However, we do know that no additional toilets were installed between baseline and endline and that people, in general, did not go out more often. Use of shared sanitation at night is the only outcome for which the effect on the endline dummy is positive. In all other difference-in-difference estimations on nighttime activities, the time dummy is actually negative.

Columns 11 and 12 report the effect of treatment on respondents' agreement with the two prompts about how likely they are to leave their house at night if the area in front of the door is well lit and if the informal settlement is well lit. In both cases, we find a statistically significant effect of treatment assignment on agreement with these statements in paths ($p < 0.01$), but in compounds we only find a statistically significant effect on how likely respondents are to leave the house at night if the area in front of the door is well lit ($p < 0.05$). While about 17% of control group respondents in paths and about 21% in compounds agreed that they would be more likely to go out at night if the area in front of their house was more lit, 42% of path respondents and 36% of compound respondents assigned to the treatment group agreed. In paths only, the effect on agreement with the statement that one would leave the house if the informal settlement is well lit is also statistically significant, but slightly smaller with 22% of the control group reporting agreement, while 35% of the treatment group agreed. These findings suggest that, among respondents living on path segments, there are substantial discrepancies between their expectations about nighttime activities and the nighttime activities they actually report participating in outside at night, while there is a more modest discrepancy for compound respondents.

Similarly, when we asked only respondents who accepted a light, about 93% said the light made it nicer to spend time with friends or family in front of their house at night, despite the fact that we find no treatment effect on this activity when we asked about their actual behavior in the previous week.

When we re-estimate all models with binary outcomes in Table 6 using binary logistic regression, we again find very similar results. Average marginal effects are reported in Appendix D Table 5.

Table 6. Impact of treatment on nighttime activities

	Night Activity Index			Shared San. Night		Family/Friends Night		Leave House Night		Front House Night	Leave House if Lit in Front	Leave House if Inf. Set. Lit
	OLS	**OLS (Short)**	**DiD (Short)**	**OLS**	**DiD**	**OLS**	**DiD**	**OLS**	**DiD**	**OLS**	**OLS**	**OLS**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A - Paths												
Treat (=1)	0.006	0.014	-0.069	-0.047	-0.080	0.001	-0.022	0.001	0.073	-0.015	0.252***	0.123***
	(0.212)	(0.119)	(0.141)	(0.049)	(0.060)	(0.035)	(0.061)	(0.044)	(0.054)	(0.044)	(0.043)	(0.046)
Endline (=1)			-0.470***		0.123***		-0.305***		-0.105**			
			(0.117)		(0.044)		(0.038)		(0.048)			
Treat*Endline			0.085		0.038		0.026		-0.074			
			(0.166)		(0.073)		(0.070)		(0.064)			
(Intercept)	4.668***	2.914***	3.381***	0.638***	0.511***	0.193***	0.492***	0.352***	0.453***	0.258***	0.168***	0.225***
	(0.132)	(0.079)	(0.094)	(0.030)	(0.035)	(0.023)	(0.037)	(0.033)	(0.037)	(0.027)	(0.025)	(0.026)
Adj. R^2	-0.002	-0.002	0.021	0.000	0.020	-0.002	0.094	-0.002	0.018	-0.002	0.076	0.016
Num. obs.	425	425	830	424	817	425	830	425	824	425	425	425
Clusters	112	112	112	112	112	112	112	112	112	112	112	112
Panel B - Compounds												
Treat (=1)	-0.779**	-0.377*	0.163	-0.169*	-0.011	-0.104	-0.034	0.065	0.017	-0.065	0.156**	0.091
	(0.342)	(0.213)	(0.245)	(0.086)	(0.084)	(0.064)	(0.092)	(0.078)	(0.076)	(0.064)	(0.077)	(0.073)
Endline (=1)			-0.132		0.303***		-0.224***		-0.146*			
			(0.170)		(0.064)		(0.071)		(0.079)			
Treat*Endline			-0.508*		-0.153		-0.070		0.040			
			(0.294)		(0.103)		(0.119)		(0.114)			
(Intercept)	5.156***	3.091***	3.211***	0.701***	0.394***	0.247***	0.474***	0.273***	0.423***	0.260***	0.208***	0.247***
	(0.229)	(0.153)	(0.195)	(0.052)	(0.051)	(0.044)	(0.068)	(0.051)	(0.053)	(0.050)	(0.048)	(0.050)
Adj. R^2	0.022	0.016	0.020	0.024	0.056	0.011	0.073	-0.002	0.009	-0.001	0.023	0.003
Num. obs.	154	154	302	154	295	154	302	154	297	154	154	154
Clusters	50	50	50	50	50	50	50	50	50	50	50	50

Note: Standard errors clustered at the level of randomization. The night activity index contains 18 binary input variables, which include: time wake up, time go to sleep, uses shared sanitation at night, visits spaza shop at night, visits church at night, does laundry outside at night, spends time with friends/family at night, spends time with friends/family in front of house at night, leaves house at night, latest time kids/women/men come inside for the night, outdoor activities between 6-7 pm, 7-8pm, 8-9pm, 5-6 am, 6-7 am, and 7-8 am. The short night activity index, for which we also have a baseline measure, contains 8 input variables, which include: time wake up, time go to sleep, uses shared sanitation at night, spends time with friends/family at night, leaves house at night, and latest time kids/women/men come inside for the night. All time variables are coded such that dark hours are coded as 1, and light hours are coded as 0. For columns 11 and 12, the outcome variables were recoded as binary variables such that 'Strongly agree' and 'Somewhat agree' were recoded as 1 and 'Neither agree nor disagree', 'Somewhat disagree', and 'Strongly disagree' were recoded as 0. ***p < 0.01; **p < 0.05; *p < 0.1.

6.4 SOLAR PUBLIC LIGHTING HAS NO EFFECT ON REPORTED EXPERIENCES OF CRIME

Table 7 shows the impact of treatment on experiences of crime. We analyze crime in three ways. First, at the household level, we create a binary indicator of whether the respondent or someone in the household experienced one of four crimes: robbery, vandalism, burglary, and physical attack (outside). We create an experience of crime count index from the sum of these binary variables that ranges from 0-4. In the regression analysis of individual outcomes, we focus on vandalism and burglary, rather than physical attacks and robberies, because they happen to the specific structure that did or did not receive a light depending on treatment group. In paths, we find no treatment effect on experiences of crime, both in the aggregate (index) or on vandalism and burglary, individually (columns 1-4 and 7, Panel A). In compounds, we find a significant decrease in crime using the short version of the experience of crime index (column 2, Panel B), however, since we find no effect on vandalism or burglary (columns 4 and 7), it is likely that these findings can be explained by the fact that there were significant differences between treatment groups at baseline.

For paths and compounds, we report the difference-in-difference using a shortened version of the experience of crime index (column 3) — which does not include burglary — because at baseline we asked about experiences of crime in the previous 12 months, while at endline we asked about the previous six months (i.e., the intervention period). The difference-in-difference estimator is not significant.[71]

Second, since we can assume we know where reported vandalisms and burglaries occurred, we also analyze both crimes at the path level.[72] In columns 5 and 8, the outcome is the number of vandalisms or burglaries per path segment. In columns 6 and 9, the outcome is a binary variable indicating whether any vandalism or burglary occurred on the path segment or not. These regressions allow us to check for displacement of burglaries or robberies to one particular experimental group or another. While intuition might suggest that lighting shifts crime from lit to unlit path segments (and hence an overestimation of the effect of lighting), a recent paper by Chalfin et al (2020) suggests that the opposite is also plausible if lit paths attract more pedestrians, i.e., potential victims. We find no effect of treatment on vandalism or burglary in paths or compounds.

Third, since we asked respondents who personally experienced a robbery or physical attack about the time of day and to point out on a map where it happened, we also analyze crime counts at

[71] At baseline, we planned the intervention to last for 12 months. Due to project delays, many of which were caused by the COVID-19 pandemic, we ultimately shortened the intervention timeline to 6 months, hence why we ask about different intervals at baseline and endline.

[72] If a person moved very shortly before the endline survey it is possible they experienced the vandalism or burglary at their previous house.

the path level and by time of day. We combine these into a night crimes and a day crimes outcome variable. As with vandalism and burglaries, this information allows us to check for displacement of robberies and physical attacks to one experimental group or another. For these variables, due to limited detail of the mapped crime points, we could only assign crimes to paths. For the same reasons that the analysis of the impact of the intervention on crime rates is limited (i.e., sample size, crime reporting, data availability, and study length, see Section 2.3), so is our test for crime displacement. We find no path-level treatment effect on day or night crimes (columns 10-13, Panel A).

Lastly, despite one or two households refusing a light for fear that it would attract crime, when we asked respondents about their perceptions of the solar public lights only about 10% across both treatment groups believe the solar lights attract criminals to paths with lights at night.

We re-estimate all models with binary outcomes in Table 7 using binary logistic regression and find very similar results. Average marginal effects are reported in Appendix D Table 6.

Table 7. Impact of treatment on experiences of crime

	Exp. of Crime Index			Vandalism			Burglary			Day Crimes		Night Crimes	
	OLS	OLS (short)	DiD	OLS	OLS (count)	OLS (bin)	OLS	OLS (count)	OLS (bin)	OLS (count)	OLS (bin)	OLS (count)	OLS (bin)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A - Paths													
Treat (=1)	-0.032	-0.046	-0.055	-0.019	-0.036	-0.021	0.016	0.101	0.091	0.172	0.070	-0.037	-0.011
	(0.069)	(0.055)	(0.097)	(0.017)	(0.065)	(0.060)	(0.027)	(0.101)	(0.084)	(0.161)	(0.089)	(0.095)	(0.078)
Endline (=1)			-0.258***										
			(0.071)										
Treat*Endline			0.001										
			(0.106)										
(Intercept)	0.369***	0.295***	0.564***	0.041***	0.138***	0.123***	0.074***	0.246***	0.215***	0.338***	0.277***	0.262***	0.215***
	(0.047)	(0.035)	(0.067)	(0.013)	(0.048)	(0.041)	(0.017)	(0.062)	(0.051)	(0.074)	(0.056)	(0.067)	(0.051)
Adj. R^2	-0.002	-0.001	0.031	0.000	-0.006	-0.008	-0.002	0.000	0.002	0.003	-0.003	-0.008	-0.009
Num. obs.	425	425	830	425	114	114	423	114	114	114	114	114	114
Clusters	112	112	112	112			112						
Panel B - Compounds													
Treat (=1)	-0.195*	-0.169**	-0.259*	-0.026	-0.032	-0.032	-0.026	-0.054	-0.179				
	(0.104)	(0.068)	(0.137)	(0.031)	(0.086)	(0.086)	(0.061)	(0.199)	(0.123)				
Endline (=1)			-0.289**										
			(0.131)										
Treat*Endline			0.089										
			(0.150)										
(Intercept)	0.390***	0.273***	0.566***	0.052**	0.115*	0.115*	0.117***	0.346***	0.346***				
	(0.065)	(0.057)	(0.116)	(0.025)	(0.064)	(0.064)	(0.032)	(0.095)	(0.095)				
Adj. R^2	0.019	0.028	0.058	-0.002	-0.018	-0.018	-0.005	-0.019	0.022				
Num. obs.	154	154	302	153	50	50	154	50	50				
Clusters	50	50	50	50			50						

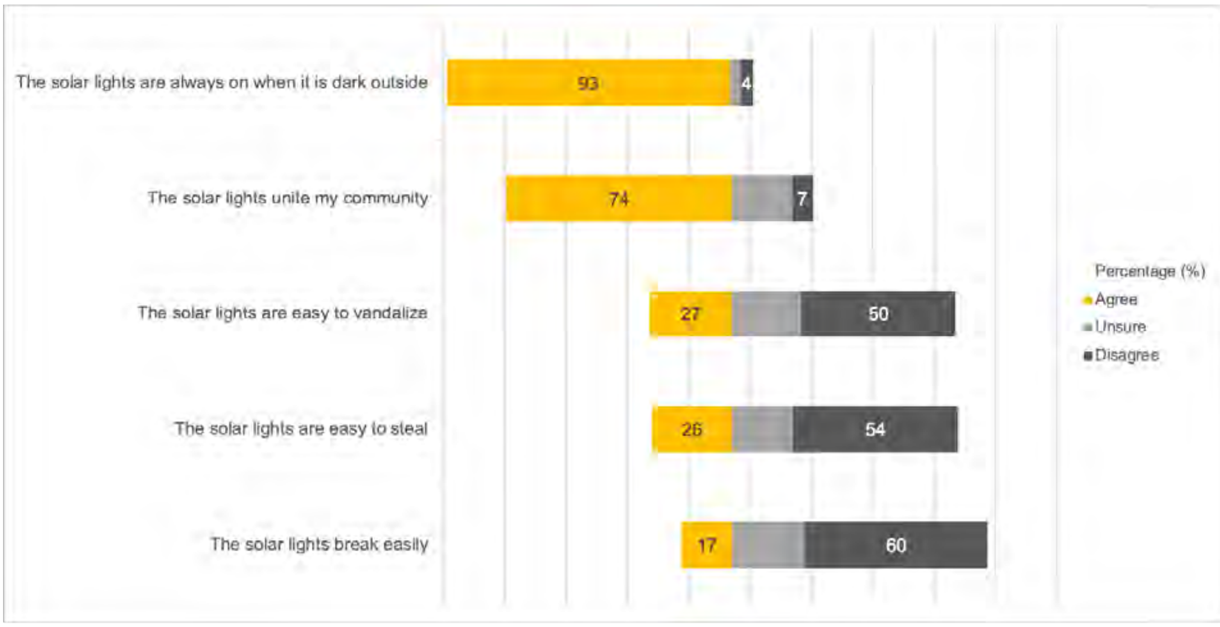
Note: Standard errors clustered at the level of randomization. Standard errors clustered at the level of randomization. The experience of crime index is made up of 4 input variables, which include experience of robbery in the previous 6 months, experience of physical attack (outside) in the previous 6 months, experience of vandalism in the previous 6 months, experience of burglary in the previous 6 months. The short version of the experience of crime index does not include burgarly and the questions ask about the previous 12 months. Column 3 reports the difference-in-difference between baseline and endline in order to show that there is no differential treatment effect despite the difference in the way we asked the question. Columns 5-6 and 8-13 are all aggregated at the cluster level, such that the count outcome is the number of occurrences per cluster and the binary outcome indicates whether any crime occurred on that cluster or not. ***p < 0.01; **p < 0.05; *p < 0.1.

6.5 EXPERIENCE AND SUSTAINABILITY OF THE SOLAR PUBLIC LIGHTS

Overall, we find high satisfaction with the solar public lighting intervention among households in both treatment groups. When asked to rate, on a scale from 0 – 10, whether households would recommend the lights to another informal settlement, treatment is associated with a statistically significantly higher score — 8.38 in the treatment group and 7.75 in the control — however both scores are reasonably high.

We also asked respondents in the treatment group who accepted a light various questions about their direct experience with the light. About 92% of respondents agreed that the light made it difficult to renovate their house, which often requires removing the entire system and reinstalling it after the renovation is complete (Appendix D Figure 4). Figure 3 shows that the majority of respondents in the treatment group agree that the lights are on at night, and that the lights unite the community. At the same, the majority disagrees that the lights are easy to steal and that they break easily. Still, about 50% either think the lights are easy to vandalize or are unsure. We also asked the questions in Figure 3 to the control group, and find results are similar (Appendix D Figure 5).

Figure 3. Opinions about the solar public light among the treatment group



The graph shows how much respondents assigned to the treatment group agree with each statement on the left. The results for the control group are similar, except the share of respondents saying they are unsure is larger (Appendix D Figure 5).

Respondents in both groups reported a high level of individual and community ownership of the lights, despite the fact that they are public lights. About 84% of the treatment group and 72% of the control group said individual households were among those responsible for taking care of the lights and 41% of the treatment group and 46% of the control group also agreed the entire community was responsible for the lights. Despite the visible presence of a maintenance team, just 20% of the treatment group and 13% of the control group list the maintenance team as one of the responsible parties. Similarly, 16% of respondents in both groups believe the leaders of the informal settlement are responsible for the lights. Perhaps because of this high level of personal and community ownership of the lights, relatively few lights were stolen or vandalized, despite the fact that many stakeholders, including community members, were concerned about theft and vandalism.

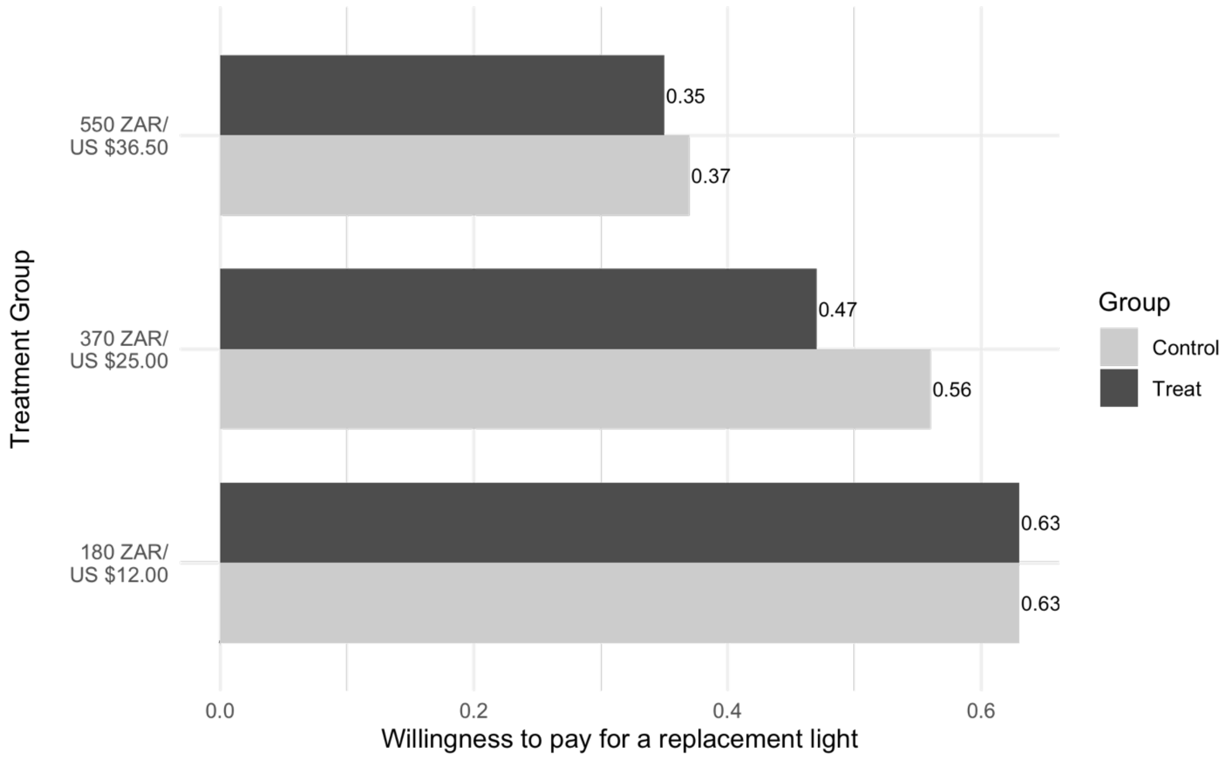
Even though ownership is high and theft and vandalism are low, the question is still whether providing public lighting on private houses would be financially sustainable. Public lighting is a public service that is generally provided by the government. We still asked respondents whether they personally would be willing to purchase a replacement light if their light were to be stolen or vandalized.[73] The reason we did not ask about willingness to fund lighting through an increase in taxes (as for example Willis et al. (2005) and Kaplan and Chalfin (2021) do) is that the population in informal settlements is generally extremely poor, often informally employed, and unlikely to pay any income tax at all (SARS, 2021).[74]

To determine willingness to pay (WTP), respondents were randomly assigned to one of three different replacement costs: 180 ZAR/US $12, 370 ZAR/US $25, 550 ZAR/US $36.50. The middle price level represents the approximate cost of the actual light used in the intervention, the low price is approximately half the cost of that light, and the high price is the approximate cost of a similar, but higher quality light. We find no difference across treatment groups in WTP, but as Figure 4 shows, we find about 63% of respondents are willing to pay US $12, about 52% are willing to pay US $25, but only 36% are willing to pay US $36.50 (Appendix D Table 7).

[73] At a community meeting announcing the solar public lighting installation process, we made clear that the solar public lights would be offered for free, but that if the light was stolen or vandalized it would not be replaced. Prior to installing the light, households that accepted a light were told that if the light broke the maintenance team would do its best to repair the light, but if the light was vandalized or stolen, it would not be replaced. During the intervention phase, this rule was enforced so most people in the community understood the consequences of theft or vandalism, hence why we structured the question this way.

[74] According to the South African Revenue Service, the threshold for paying personal income tax in 2021 was 83,100 ZAR for people under 65.

Figure 4. Willingness to pay for a replacement solar public light



The graph shows the share of each group that is willing to pay the randomly shown price for a replacement light.

As these numbers are only stated rather than revealed preferences, and hence actual WTP might be lower, they provide an indication that residents in this community do not view the solar public lights as a purely public service and residents in both the treatment and control groups value their presence in the community.

6.6 HETEROGENEITY

We analyze heterogeneous impacts of the solar public lighting treatment by gender (of the respondent) and by distance of the respondent's structure to the nearest high-mast light on a selection of the most important outcomes presented in the main analysis. If, as some literature suggests, women are particularly fearful at night, we would expect to see a stronger impact of solar public lighting on women's perception of safety, in particular. Appendix D Table 8 reports the heterogeneous effects for gender in both paths and compounds. In paths (Panel A), however, there is no evidence of differences between men and women. Although we do see that despite the increase in safety in the path where respondents live at night associated with the treatment, women in both experimental groups still feel significantly less safe than men.

Women in both groups also have a significantly lower score in the night activity index and are significantly less likely to report going outside to use shared sanitation at night. In compounds (Panel B), the situation is slightly different. We find that women overall perceive a 14% higher risk of burglary, but although women in the treatment group still perceive a higher risk of burglary, the effect is smaller (8%) than for women, overall. Outside of this, we do not find a stronger effect of treatment for women on any other outcome, though we do learn that women who live in compounds, in both groups, are significantly less likely to report feeling safe in the informal settlement during the day. It is possible that this is one reason why these women have chosen to live in a compound, rather than directly on a path, in the first place.

Distance from the nearest high-mast light is determined by calculating the Euclidean distance between each front door and each of the two high-mast lights. For each house, we keep the smaller of the two distances, measured in meters. Since much of the literature finds diminishing returns beyond a certain (as yet undetermined) level of brightness (Boyce, 2019; Fotios & Castleton, 2016; Svechkina et al., 2020), we do not expect to find stronger treatment effects for those living close to one of the high-mast lights. Rather, since those who live farthest from the high-mast lights tend to also live farthest from the central institutions within the neighborhood (the largest Spaza shop, the largest collection of toilets, etc.), we would expect the treatment to somewhat mitigate any negative effects of living far from a high-mast light and therefore, possibly, also far from the neighborhood's so-called center of gravity. Appendix D Table 9 reports the results of our test for heterogeneous effects on distance to the nearest high-mast light in both paths and compounds. In paths (Panel A), we find that while treatment is linked to a significant decrease in perceived risk of burglary, the decline gets smaller as distance from the nearest high-mast light increases, indicating that those who live further from high-mast lights experience a muted effect. We find no other heterogeneous effects in paths for the other outcomes we study and no heterogeneous effects of distance to the nearest high-mast light in compounds (Panel B).

7 ROBUSTNESS CHECKS

7.1 NON-COMPLIANCE

We have so far analyzed the intention-to-treat effect and the differential effect of treatment assignment on the five categories of outcomes we are interested in: effectiveness of the solar public light, perception of safety, perceived risk of crime, willingness to engage in public space through nighttime activities, and experience of crime. As noted in Section 5.2, however, we do not have perfect compliance with treatment assignment. First, the pre-existing high-mast lights generally provide light to those houses located closest to each light, and hence also control paths. Second, as in most experiments, eligible households had the option to refuse the light. In our case, we had a 94% take-up rate, so most accepted, still about 19 houses did not want the light. Even if someone did not want the light, they may have still lived in a lit path or compound if their neighbors were offered a light and accepted. Finally, the last source of non-compliance is theft and vandalism, since these lights were not replaced. Again, these houses may have no longer had a light on their house, but likely continued living in a lit path or compound.

These examples of treatment non-compliance are potential sources of bias in the estimations presented above. In order to determine the robustness of our main findings, we follow the example of many other researchers and use an instrumental variables approach (e.g., Devoto et al., 2012), where treatment assignment is the instrument, which satisfies the requirement that it is correlated with actually receiving the treatment by design and, we argue, satisfies the exclusion restriction because the randomization only effects our outcomes of interest via the treatment. In the first stage, our dependent variable is the endline average lux at the path or compound level, which captures variation in light intensity.

Appendix D Table 10 reports the first stage estimation (column 1) and the LATE on respondent perception of brightness (Appendix D Table 10, columns 1-3), on perception of safety (Appendix D Table 10, columns 4-11), perception of crime risk (Appendix Table 10, columns 12-13), nighttime activities (Appendix D Table 10, Cont'd, columns 1-8), and on experiences of crime (Appendix D Table 10, Cont'd, columns 10-12). Similar to the OLS regression, the LATE on perception of brightness in paths is positive and significant for all three outcomes in paths, but only the first two outcomes in compounds. An increase in lux of 1 (note that on average treatment paths are 12.5 lux brighter than control paths) leads to a 5.5 percentage point increase in perceived brightness in front of the house in paths and 4.7 percentage point increase in compound. In paths, an increase in lux of 1 leads to a 5.3 percentage point increase in perceived brightness in the path where the person lives, whereas in compounds the increase is 3.6 percentage points. In terms of the perception that the informal settlement is well lit, an increase of 1 lux leads to a 1.2 percentage point increase in paths and no effect in compounds. In paths, we also find an additional unit of lux leads to an increase in perceived safety in both the extended and short perceived safety indices and a .09 percentage point increase in perceived safety in the path where the respondent lives at night. In paths, we also find a significant decrease in perceived risk of burglary.

Again, we find no effect on perceived safety in compounds and no effects on nighttime activity or experience of crime in either paths or compounds. Hence, these results indicate that our main results do not suffer unduly from bias caused by treatment non-compliance.

7.2 SPILLOVER EFFECTS

Since we could only cover a single neighborhood in this field study due to the community engagement required to work in informal settlements (at night) in South Africa, spillovers are a major threat to identification. By design, spillovers were unavoidable in this experimental set-up given that it was not feasible to randomize at a higher neighborhood level (see Section 3.2) and we therefore had to randomize at the path segment and compound level. Spillovers could occur because all residents are free to use any path segment or visit (almost) any compound they wish, therefore all residents experience the treatment, but to different extents.

While we could not control experientially for spillover (e.g., Egger et al., 2019), we made sure that no light from a treated path segment or compound could directly spillover onto an untreated path segment or compound occurs. For example, households on a treatment path whose front door was close to an intersection with a control path did not receive a light to prevent light spillover onto a control path (they are still considered treatment households in the analysis because the front door faces a treatment path segment/compound). On the other hand, we expect that living near a lit path segment may affect the perception of safety and behavior of residents in nearby path segments or compounds[75] and living near an unlit path segment may also diminish the effect of the treatment. Hence, our estimated effects likely underestimate the real effect of the public light intervention.

To better understand the magnitude of these spillover effects, we define a third group called $BORDER_{ip}$, which equals 1 for any household that lives directly adjacent to a cluster of the opposite treatment status, and 0 otherwise. Therefore, we test for an effect of living *near* a treated/untreated path segment/compound to account for the fact that self-reported outcomes may be influenced by the immediately surrounding path network and not only the path segment or compound where a resident lives. To analyze spillovers, we estimate equation (6):

$$OUTCOME_{ip} = \beta_0 + \beta_1 TREAT_p + \beta_2 BORDER_{ip} + \Theta X'_{ip} + \epsilon_{ip} \tag{6}$$

where $OUTCOME_{ip}$ is the endline outcome measure for household i living on the path segment or compound p; $TREAT_p$ is an indicator for a path segment or compound assigned to the public lighting intervention (and zero otherwise); $BORDER_{ip}$, as explained above, is a dummy variable indicating the “spillover” treatment group, where 0 is the control group, 1 is the treatment group, and 2 is the border group; and ϵ_{ip} is the standard error clustered at the level of randomization (path segment/compound).

Appendix D Table 11 reports both the treatment effect and the effect of being in the *border* group on several endline outcomes of interest. Using this approach, we do not find widespread evidence for spillover on most outcomes.

7.3 MULTIPLE-HYPOTHESIS TESTING

Since we test several different outcomes, we account for multiple hypothesis testing using the Bonferroni adjustment. Assuming 34 outcomes in the analysis of paths and 30 outcomes in the analysis of compounds, we report the adjusted p values in Appendix D Table 2. After the adjustment, in paths, the effects documented on the perception that the informal settlement is well lit, the effect on both safety perception indices, and the effects on perception of safety in the informal settlement during the day and night are no longer significant even at the 10% level.

[75] Blattman et al. (2019) encounter a similar dynamic in which spillovers cannot be avoided in the study design.

The effects on endline average lux, perception that the front of the house is well lit, perception that the path is well lit, perception of safety in the path at night, and the perception that a respondent would be more willing to leave the house at night if the area in front of their home is well lit all remain significant. In compounds, endline average lux, the perception that the front of the house is well lit, and the perception that the path is well lit all remain significant, while the effects on the night activity index, the perception that a respondent would be more willing to leave the house at night if the area in front of their home is well lit, and the effect on the experience of crime index are no longer significant.

8. DISCUSSION

8.1 CONTEXTUALIZING THE RESULTS

The results of this field experiment present evidence that solar public lighting can provide effective light at night in informal settlements. While it may seem obvious that installing more lights would result in higher light levels, it is not as trivial a finding as it seems. Many stakeholders, including residents of the informal settlement, were worried about vandalism and theft of the lights as well as general maintenance, yet there were relatively few instances of either. In addition, in the absence of an objective lighting standard for informal settlements, the fact that respondents' subjective perceptions of brightness levels corroborate the objective average lux measure indicates that the increase in light levels is practically as well as statistically significant. This result is important given that the settlement already has high-mast lighting, which our lux measurements show is unevenly distributed throughout the neighborhood (see Article 3).

We also find suggestive evidence that higher levels of lighting lead to a 19% percentage point increase in perceptions of safety overall for residents living in paths, but we find no effect in compounds. The absence of an effect in compounds may be due to the fact that a) those living in compounds may already have been more concerned about safety, hence the formation of the compound, and b) the compound connects to a path that may or may not have been treated, meaning compound respondents may still have felt quite insecure leaving their lit compound. The finding that residents in paths feel safer at night lends support to what has been found by previous observational studies (Atkins et al., 1991; Blöbaum & Hunecke, 2005; Boyce et al., 2000; Kaplan, 2019; Kaplan & Chalfin, 2020; Nair et al., 1997; Nasar & Jones, 1997; Peña-García et al., 2015; Roman & Chalfin, 2008; Svechkina et al., 2020; Vrij & Winkel, 1991; Wu & Kim, 2018). Furthermore, we find that the treatment has a positive and significant impact on path respondents' perception of safety in the informal settlement, broadly, both during the day (10.5 percentage points) and at night (6 percentage points). In actuality, though, perceptions of safety are still relatively low, with only 52% of the treatment group reporting feeling safe during the day and 19% feeling safe at night. When we ask about perception of safety in the path where the respondent lives, we find no effect of treatment on perception of safety during the day, but a statistically significantly 10.7 percentage point increase in the number of residents who report feeling safe in their path at night — double the control group. We find no difference between treatment groups in perceptions of safety inside the home at night, however, it is worth noting that just 44% of the control group and 51% of the treatment group report feeling safe in their own homes at night. These results underscore the level of insecurity felt by residents living in this informal settlement, indicating that lighting leads to a significant, but likely not sufficient improvement in feelings of safety for residents of informal settlement, given the large number of other factors that can influence these perceptions.

Perhaps not surprisingly then, greater perceptions of safety do not necessarily translate to widespread changes in behavior or experiences of crime. In paths, we find no effect of the treatment on the index of reported nighttime activity (extended or short), however, we do find an effect on respondents' expectations about their willingness to leave the house at night. In compounds, we actually find a negative effect of treatment on the two nighttime activity indices, as well as on the use of shared sanitation at night, yet positive effects on respondents' expectation that they will go out more if the front of the house is well lit. This discrepancy between reported nighttime activities and residents' expectations about the influence of light on their lives is consistent with our findings on perception of safety. Kaplan and Chalfin (2021) conduct a Mechanical Turk survey experiment to test the effect of hypothetical brighter street lighting in Chicago, Illinois and conclude that people do not change nighttime behavior in response to brighter light, however, these findings are primarily based on vignettes and a question about how many nights respondents expect to go out per week. These questions are similarly hypothetical to the two outcomes for which we do find significant treatment effects. Though we arrive at similar conclusions, the difference in approach also highlights how responses to a physical intervention may differ from a hypothetical one.

In our setting, residents may not participate in significantly more nighttime activities either because they do not feel safe enough to do many more things at night, because the intervention was not long enough to realize substantial behavioral changes, or because people simply do not want to be outside more at night. When we look at the three individual nighttime activities — use of shared sanitation at night, going out with friends or family at night, and whether or not respondents leave the house at all at night — and use a difference-in-difference estimation, we find no treatment effects, but find that the time dummy on going out with friends/family and on leaving the house at night is negative, whereas it is positive and significant with respect to the use of shared sanitation at night (both paths and compounds). This finding indicates that over time (between baseline in March 2019 and endline in May/June 2021) residents are less likely to go out at night for social activities, but more likely to go out at night to use the toilet. We cannot say whether this increased use of sanitation is due to the impact of the intervention spilling over onto the control group or some other time trend. However, spillover is likely. When we discussed the results for shared sanitation with local field staff they were not surprised because there is a lot of shame associated with using a bucket or other in-home toilet alternative. Therefore, any improvement in lighting in the settlement could lead to an increased use of sanitation.

For policymakers, the takeaway is that better public lighting likely enables access to shared sanitation infrastructure, which is a basic need. But more research is needed: particularly a larger-scale study that randomizes across informal settlements to eliminate spillover effects.

In contrast, even though we cannot completely rule out spillover effects for other nighttime activities, the fact that they generally decrease over time indicates that the null effect between the treatment and the control group for nighttime activities is not likely to be driven by spillover effects. Moreover, when we looked at the border group — those living adjacent to a cluster of the opposite treatment status — we find no systematic evidence of spillover to this group.

We also find no consistent evidence that lighting affects reported experiences of crime, however, this was expected given the relative rarity of crime (even in a high-crime area), the study sample size, and possible reporting bias (if respondents were afraid to be honest about crime experiences). Thus, our findings should not be interpreted to mean that lighting does not affect experiences of crime, but rather that a larger sample size is essential to conclude either way. Furthermore, any effect of light on crime would likely only be a small part of the story, as many other factors influence crime. For context, leading up to the intervention, Khayelitsha has seen a rise in gang activity, with gang members frequently demanding "protection money" and threatening physical harm if the money is not paid. This situation creates an enormous amount of fear about going out at night that is not related to the lighting. Although it would have been useful to ask about this at endline, the issue is sensitive as some respondents may actually be gang members (or relatives), thus we could not account for this in our estimates.

8.2 CONTRIBUTION TO THEORY

As discussed in Section 2, there are two main mechanisms through which light is theorized to affect nighttime life:[76] 1) either via the direct effect of brighter, more uniform lighting which provides visibility and opportunities for surveillance (Cozens et al., 2005; Farrington & Welsh, 2002); and/or 2) via the investment and care in the community that improvements in environmental design (i.e., lighting infrastructure) may signal. The first channel should only lead to effects at night, while the community investment channel should lead to effects during the day and at night (Chalfin et al., 2021; Cozens et al., 2005; Farrington & Welsh, 2002). In their RCT, Chalfin et al. (2021) find evidence in support of the community investment channel, documenting a reduction in both daytime and nighttime crimes in response to the introduction of flood light towers. While we also leverage variation in lighting intensity to estimate effects, we cannot study the impact of light on crime in a comparable way, therefore we focus primarily on effects on perception of safety, which Chalfin et al. (2021) do not study.

[76] As mentioned in Section 2 there are other theories specifically related to crime, but these theorized channels most pertain to non-crime outcomes.

We find that in paths treatment is associated with an increase in perceived safety in the informal settlement, broadly, during both the day and night, which would support the community investment channel. Chalfin et al. (2021) speculate that the visibility of the lights they study as well as the presence of maintenance personnel may have contributed a crime deterrent effect. Similarly, our results may be attributable, not only to the visibility of the lights, but to the presence of the maintenance team, who responded to service requests and periodically checked that all lights were working. On the other hand, we find that the treatment is only associated with a significant increase in perception of safety in paths at night. These findings complicate the community investment interpretation. It is possible that the dominant mechanism is dependent on the scale at which the outcome variable is measured and we cannot rule out either mechanism based on this study.

8.3 LIMITATIONS

Since blinding is not possible in a study where people receive a light installed on their front door, social desirability bias in survey responses is (always) a concern. To manage expectancy or social desirability bias, all household survey data (collected March 2019) were gathered before the lighting intervention was announced. While it was unavoidable that the topic of light came up in the survey, we did not link our data collection to any future intervention.

When we announced the lighting intervention in February 2020, we explained to the entire community, regardless of treatment status, that the project would run in two phases and that houses who did not receive a light in the first phase would receive one in the second. In this way, households should not have been incentivized to adjust their responses at endline, since the control group knew it would receive a light and the treatment group knew they could keep their lights. We also made clear that no stolen or vandalized lights would be replaced.

Since we worked within a single neighborhood and community support for the field study was essential, the respondents were aware that the endline survey is linked to the intervention, in that we wanted to know their opinion of the lights. However, residents did not know the specific hypotheses being tested. To further minimize priming, we asked all questions related to satisfaction with the lights at the end of the survey. Furthermore, since the community cannot influence the lux measurements, we have a measure that is not vulnerable to experimenter demand or social desirability bias. The last reason we are less concerned about social desirability bias is the nature of the treatment itself. Although the lights are installed on individual houses, the use of the light is available to the public. Thus, we are not concerned that people will link their answers about safety perception to whether they directly received a light or not.

Finally, it is impossible to ignore the impact that the COVID-19 pandemic has had on the residents of the informal settlement we study. Since we conducted the baseline survey one year prior to the onset of COVID-19 pandemic and the endline one year after, we cannot rule out that self-reported responses about nighttime activity, perception of safety and crime risk, and experiences of crime are in some way directly or indirectly affected by the pandemic. That said, since the pandemic impacts all residents of the informal settlement, the significant effects we did find may be underestimations.

9. CONCLUSION

Public lighting is ubiquitous in the vast majority of formal cities; indeed, it is easy to take for granted. Yet, only one other RCT studies the impact of public lighting infrastructure, while only a small number of studies rigorously study the impact of ambient lighting, exploiting variation caused by public light outages or DST. None of these studies take place in informal settlements, where public lighting is usually an afterthought. Our study provides the first experimental evidence of the impact of public lighting in the context of an informal settlement, a form of urban neighborhood that is only becoming more numerous alongside rapid urbanization.

The results of our study demonstrate two types of findings. First, we show that even in the presence of high-mast lights, a common form of public lighting in South African informal settlements, solar public lights positively and significantly improve the availability of light on paths and compounds that received lighting. Importantly, especially to residents and policymakers, theft and vandalism were relatively minor. Second, the provision of this additional lighting results in respondents feeling safer overall, particularly at night, where baseline levels of perception of safety were very low. While we do not demonstrate a treatment effect of additional lighting on residents' willingness to spend time in public space at night, we find that residents in both groups appear to be more likely to report using shared sanitation at night over time. These findings are important for the academic literature, as they support previous findings. They are also important for policymakers, who now have evidence of an alternative to high-mast lighting and standard streetlighting in informal settlements that can improve perceptions of safety and likely enhances access to shared sanitation.

Importantly, although we do not find any effect on crime, we cannot be sure if that is due to an actual absence of an effect, our limited sample size, or measurement error. There is no way to know if a respondent held back such information out of fear or embarrassment. Police crime statistics may not have drastically improved our estimations as field staff said that many crimes, especially robberies, are never reported to the police because residents feel it is a waste of time.

Similar to the vast majority of field experiments, external validity of the results is not clear. In sub-Saharan Africa, South Africa is often considered an outlier because it is a middle-income country, while many other countries with large numbers of informal settlements are much lower income overall. Yet, we argue that our experiment, if anything, underestimates effects as the study site already had some form of public lighting. In informal settlements that are either not surrounded by formal areas with standard streetlighting or do not have any residential public lighting, it is plausible to expect the impact would have been larger.

Finally, the results of this study provide useful additional evidence that informs both the theoretical and empirical research on the impact of light at night. Although we cannot conclusively determine the channel through which light affects life at night, we provide evidence from a new context that can form the foundation for future work, particularly a larger study across several informal settlements. Furthermore, our study underscores the importance of designing infrastructure solutions that fit the particular characteristics of informal settlements. Importantly, we also show that experimental research on public lighting and the lived experience of people in informal settlements is possible and necessary.

10. APPENDIX D

Figure 1. A high-mast light in the informal settlement

Figure 2. Randomization approach

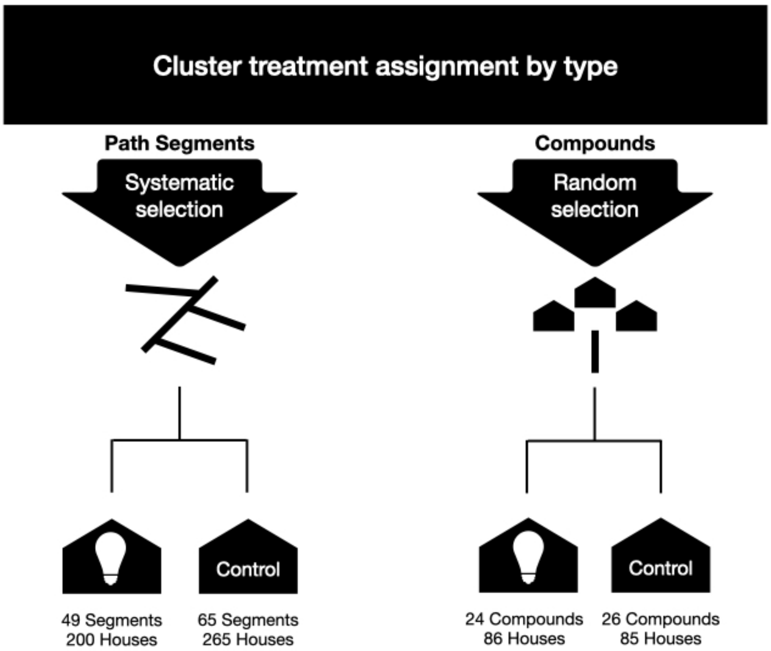


Figure 3. The solar public light installed on a household living on a treatment path

Table 1. Construction of indices at baseline and endline

Index	Baseline Inputs	Endline Inputs	Coding
Perception of Safety Index	Do you feel safe when you are outside in your neighborhood during the daytime?	Do you feel safe when you are outside anywhere in your neighbourhood during the daytime?	Always, Most of the time, About half the time = 1; Never, Rarely = 0
	Do you feel safe when you are outside in your neighborhood at night?	Do you feel safe when you are outside anywhere in your neighbourhood at night?	Always, Most of the time, About half the time = 1; Never, Rarely = 0
		Do you feel safe when you are outside in the path in front of your house during the daytime?	Always, Most of the time, About half the time = 1; Never, Rarely = 0
		Do you feel safe when you are outside in the path in front of your house at night?	Always, Most of the time, About half the time = 1; Never, Rarely = 0
		Do you feel safe when you are inside your house during the daytime?	Always, Most of the time, About half the time = 1; Never, Rarely = 0
		Do you feel safe when you are inside your house at night?	Always, Most of the time, About half the time = 1; Never, Rarely = 0
		I feel safe walking to the toilet alone at night.	Strongly Agree, Somewhat Agree, Neither Agree nor Disagree = 1; Somewhat Disagree, Strongly Disagree = 0
		I feel safe walking to the nearest spaza shop alone at night.	Strongly Agree, Somewhat Agree, Neither Agree nor Disagree = 1; Somewhat Disagree, Strongly Disagree = 0
		I feel safe walking to visit a friend of family member somewhere else in the informal settlement alone at night.	Strongly Agree, Somewhat Agree, Neither Agree nor Disagree = 1; Somewhat Disagree, Strongly Disagree = 0
		I feel safe walking home from church alone at night.	Strongly Agree, Somewhat Agree, Neither Agree nor Disagree = 1; Somewhat Disagree, Strongly Disagree = 0
	What private source(s) of light do you use when you go outside of your house after sunset?	What private source(s) of light have you used during the last week when you were walking outside at night.	Any light selected = 0; Never went outside = 0; None = 1
Nighttime Activity Index	Today, what time did you wake up?	Today, what time did you wake up?	Dark times = 1; Daylight times = 0
	Yesterday, what time did you go to sleep?	Yesterday, what time did you go to sleep?	Dark times = 1; Daylight times = 0
	How do you use the toilet after sunset?	How do you use the toilet at night?	Walk alone, Somebody walks with me = 1; Do not need toilet, Flush toilet, Portable toilet, Bucket in house = 0
		Do you ever go to the Spaza shop for any reason at night	Yes = 1, No = 0
		Do you ever go to church for any reason at night	Yes = 1, No = 0
		In the last week, on how many days did you go outside at nighttime to do washing?	Response > 0 = 1; 0 = 0
	In the last 7 days, did you go outside at nighttime to spend time with friends or family members?	In the last week, did you go outside anywhere at nighttime to spend time with friends or family members?	Yes = 1; No = 0; I do not have friends/family = 0
		In the last week, on how many days did you spend time in front of your house at nighttime?	Response > 0 = 1; 0 = 0
	Last night, how many times did you leave the house at nighttime?	Last night, how much time did you spend outside your house at nighttime?	Response > 0 = 1; I never went outside at night = 0
	When is the latest time that children in this household are allowed to be outside in the evening?	When is the latest time that children in this household are allowed to be outside in the evening?	Times after 8 pm/No specific time = 1; Times before 8 pm = 0
	When is the latest time that women in this household are allowed to be outside in the evening?	When is the latest time that women in this household are allowed to be outside in the evening?	Times after 8 pm/No specific time = 1; Times before 8 pm = 0
	When is the latest time that men in this household are allowed to be outside in the evening?	When is the latest time that men in this household are allowed to be outside in the evening?	Times after 8 pm/No specific time = 1; Times before 8 pm = 0
		Activities between 6 - 7 pm	Outdoors activities = 1; Indoor activities = 0
		Activities between 7 - 8 pm	Outdoors activities = 1; Indoor activities = 0
		Activities between 8 - 9 pm	Outdoors activities = 1; Indoor activities = 0
		Activities between 5 - 6 am	Outdoors activities = 1; Indoor activities = 0
		Activities between 6 - 7 am	Outdoors activities = 1; Indoor activities = 0
		Activities between 7 - 8 am	Outdoors activities = 1; Indoor activities = 0
Experience of Crime Index	Have you or anyone in your household been robbed in the last 12 months?	Have you or anyone in your household been robbed in the last 6 months?	Yes = 1, No = 0
	Has your house ever been vandalized in the last 12 months?	Has your house ever been vandalized in the last 6 months?	Yes = 1, No = 0
	Have you or anyone in your household been physically attacked in the last 12 months?	Have you or anyone in your household been physically attacked in the last 6 months?	Yes = 1, No = 0
		Has your house ever been burglarized in the last 6 months?	Yes = 1, No = 0

Notes: If respondents answered "I don't know" or "Not applicable" the response was re-coded as NA, however, when compiling the indices NA responses were ignored (as it is a sum), therefore these observations do not drop out. For the crime experience input variables, we asked about different time intervals at baseline and endline because we originally planned for a 12-month intervention, however, due to the COVID-19 pandemic we ultimately had to adjust to a six-month intervention.

Table 2. Bonferroni adjusted p-values to account for multiple hypothesis testing

	Path				Compound			
Outcome	Treat (=1)	p.value	Bonferroni adjustment	Remains Sig. at 10%	Treat (=1)	p.value	Bonferroni adjustment	Remains Sig. at 10%
Endline Avg. Lux	12.525	0.000	0.000	**Yes**	16.045	0.000	0.000	**Yes**
Lit Front of House	0.694	0.000	0.000	**Yes**	0.753	0.000	0.000	**Yes**
Lit Path	0.675	0.000	0.000	**Yes**	0.572	0.000	0.000	**Yes**
Lit Informal Settlement	0.145	0.003	0.107	No	-0.013	0.874	1.000	
Safety Perception Index	0.660	0.023	0.782	No	-0.013	0.979	1.000	
Safety Perception Index (Short)	0.210	0.016	0.557	No	-0.182	0.217	1.000	
Safe in Inf. Sett. in Day	0.105	0.026	0.885	No	-0.104	0.236	1.000	
Safe in Inf. Sett. at Night	0.061	0.076	1.000	No	-0.091	0.139	1.000	
Safe in Path in Day	0.085	0.116	1.000		0.000	1.000	1.000	
Safe in Path at Night	0.107	0.002	0.069	**Yes**	0.026	0.724	1.000	
Safe Inside in Day	0.038	0.367	1.000		0.013	0.879	1.000	
Safe Inside at Night	0.071	0.188	1.000		0.104	0.241	1.000	
Perceived Burglary Risk	-0.044	0.029	0.977	No	0.000	1.000	1.000	
Perceived Vandalism Risk	0.003	0.926	1.000		0.024	0.587	1.000	
Night Activity Index	0.006	0.977	1.000		-0.779	0.027	0.809	No
Night Activity Index (Short)	0.014	0.905	1.000		-0.377	0.083	1.000	
Shared Sanitation at Night	-0.047	0.346	1.000		-0.169	0.056	1.000	
Out Family/Friends at Night	0.001	0.983	1.000		-0.104	0.113	1.000	
Leave House at Night	0.001	0.979	1.000		0.065	0.412	1.000	
Front House w/ Family/Friends at Night	-0.015	0.729	1.000		-0.065	0.315	1.000	
Leave House if Lit in Front	0.252	0.000	0.000	**Yes**	0.156	0.048	1.000	No
Leave House if Inf. Sett. Lit	0.123	0.008	0.287	No	0.091	0.218	1.000	
Experience of Crime Index	-0.032	0.646	1.000		-0.195	0.068	1.000	
Experience of Crime Index (Short)	-0.046	0.401	1.000		-0.169	0.017	0.512	No
Vandalism (binary, HH-Level)	-0.019	0.259	1.000		-0.026	0.406	1.000	
Vandalism (# per path)	-0.036	0.578	1.000		-0.032	0.711	1.000	
Vandalism (binary, path-level)	-0.021	0.726	1.000		-0.032	0.711	1.000	
Burglary (binary, HH-level)	0.016	0.562	1.000		-0.026	0.673	1.000	
Burglary (# per path)	0.101	0.322	1.000		-0.054	0.786	1.000	
Burglary (binary, path-level)	0.091	0.282	1.000		-0.179	0.151	1.000	
Day Crimes (# per path)	0.172	0.288	1.000					
Day Crimes (binary, path-level)	0.070	0.431	1.000					
Night Crimes (# per path)	-0.037	0.696	1.000					
Night Crimes (binary, path-level)	-0.011	0.884	1.000					

Notes: Effects that remain significant are marked with a bold "Yes." Effects that are significant in the main results, but are no longer significant are marked with a "No."

Table 3. Marginal effects of treatment on self-reported brightness variables

	Paths			Compounds		
	Front of House	Path	Inf. Sett.	Front of House	Path	Inf. Sett.
	(1)	(2)	(3)	(4)	(5)	(6)
Treat (=1)	0.477***	0.440***	0.141***	0.446***	0.438***	-0.013
	(0.013)	(0.006)	(0.042)	(0.030)	(0.017)	(0.077)
Log Likelihood	-181.785	-175.413	-255.744	-53.694	-75.216	-99.124
AIC	367.570	354.827	515.488	111.388	154.432	202.247
BIC	375.674	362.820	523.592	117.462	160.385	208.321
N	425	402	425	154	145	154

Note: All three self-report variables are constructed as binary outcomes from variables in which respondents could answer, 'Totally dark' = 0, 'Somewhat dark' = 0, 'Not much light, but not dark' = 0, 'Somewhat lit' = 1, 'Very well lit' = 1. The table reports average marginal effects with standard errors in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 4. Marginal effects of treatment on perceived safety variables

	Inf. Sett. Day	Inf. Sett. Night	Path Day	Path Night	Inside House Day	Inside House Night	Burglary Risk	Vandalism Risk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Paths								
Treat (=1)	0.104**	0.060*	0.085*	0.104***	0.039	0.071	-0.046**	0.003
	(0.047)	(0.035)	(0.048)	(0.034)	(0.043)	(0.048)	(0.022)	(0.027)
Log Likelihood	-290.819	-180.338	-293.064	-173.643	-240.488	-292.908	-61.876	-118.218
AIC	585.639	364.677	590.127	351.287	484.977	589.817	127.752	240.437
BIC	593.743	372.781	598.231	359.391	493.081	597.921	135.856	248.527
N	425	425	425	425	425	425	425	422
Panel B - Compounds								
Treat (=1)	-0.103	-0.092	0.000	0.026	0.013	0.103	0.000	0.024
	(0.078)	(0.060)	(0.081)	(0.062)	(0.071)	(0.078)	(0.040)	(0.047)
Log Likelihood	-105.268	-67.120	-106.732	-72.930	-89.223	-104.846	-37.012	-46.592
AIC	214.535	138.240	217.463	149.860	182.446	213.692	78.023	97.184
BIC	220.609	144.313	223.537	155.934	188.520	219.766	84.097	103.231
N	154	154	154	154	154	154	154	152

Note: The table reports average marginal effects with standard errors in parentheses. The first six variables are constructed as binary outcomes from variables in which respondents could answer, 'Never' = 0, 'Rarely' = 0, 'About half the time' = 1, 'Most of the time' = 1, 'Always' = 1. The last two variables are constructed as binary outocmes from variables in which the respondent could answer, 'Not a risk' = 0, 'Small risk' = 0, 'Medium risk' = 1, 'Big risk' = 1, and 'Very big risk' = 1. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 5. Marginal effects of treatment on nighttime activity variables

	Paths						Compounds					
	Shared Sanitation Night	**Friends/ Family Night**	**Leave House Night**	**Front House Night**	**Leave House if Lit in Front**	**Leave House if Inf. Set. Lit**	**Shared Sanitation Night**	**Friends/ Family Night**	**Leave House Night**	**Front House Night**	**Leave House if Lit in Front**	**Leave House if Inf. Set. Lit**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treat (=1)	-0.046	0.001	0.001	-0.015	0.235***	0.119***	-0.166**	-0.104	0.065	-0.065	0.154**	0.091
	(0.047)	(0.039)	(0.047)	(0.043)	(0.037)	(0.042)	(0.073)	(0.064)	(0.074)	(0.067)	(0.069)	(0.072)
Log Likelihood	-281.512	-208.445	-275.930	-239.750	-233.598	-247.185	-100.161	-74.602	-94.358	-82.074	-89.820	-92.262
AIC	567.024	420.890	555.861	483.500	471.196	498.370	204.323	153.204	192.716	168.149	183.641	188.525
BIC	575.123	428.995	563.965	491.604	479.301	506.475	210.397	159.278	198.789	174.223	189.715	194.599
N	424	425	425	425	425	425	154	154	154	154	154	154

Note: The table reports average marginal effects with standard errors in parentheses. Use of shared sanitation is coded as 1 if the respondent reports walking to use shared sanitation alone or with someone at night and 0 otherwise, spending time with friends/family outside at night is 1 if the person engaged in this activity in the previous week and 0 otherwise, leave house at night is coded as 1 if the person reports going outside 1 or more times per night and 0 otherwise, spending time with friends/family in front of the house at night is coded as 1 if the respondent reports engaging in the activity and 0 otherwise. Columns 5-6 and 11-12 are recoded as binary variables such that 'Strongly agree' and 'Somewhat agree' were recoded as 1 and 'Neither agree nor disagree', 'Somewhat disagree', and 'Strongly disagree' were recoded as 0. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 6. Marginal effects of treatment on experience of crime variables

	Paths						Compounds			
	Vandalism	Vandalism (Path)	Burglary	Burglary (Path)	Day Crimes (Path)	Night Crimes (Path)	Vandalism	Vandalism (Comp)	Burglary	Burglary (Comp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat (=1)	-0.020	-0.021	0.015	0.089	0.069	-0.011	-0.027	-0.032	-0.026	-0.179
	(0.020)	(0.061)	(0.027)	(0.080)	(0.086)	(0.077)	(0.034)	(0.087)	(0.050)	(0.119)
Log Likelihood	-60.942	-40.393	-118.141	-64.047	-69.983	-58.660	-24.973	-16.182	-51.228	-27.584
AIC	125.885	84.787	240.282	132.095	143.965	121.319	53.946	36.365	106.457	59.169
BIC	133.989	90.259	248.376	137.567	149.438	126.792	60.007	40.189	112.531	62.993
N	425	114	423	114	114	114	153	50	154	50

Note: The table reports average marginal effects with standard errors in parentheses. The outcome variables in columns 1, 3, 7, and 9 are reported experiences of vandalism and burglary at the household level, coded such that if a respondent reported they experienced the crime in the previous 6 months the variable is 1 and 0 if not. The remaining outcome variables represent the occurance of the specified crime at the path level, coded such that if the crime occurred on the path at all the value is 1 and 0 otherwise. ***p < 0.01; **p < 0.05; *p < 0.1.

Figure 4. Perceived impacts of the solar public lights amongst those who accepted a light

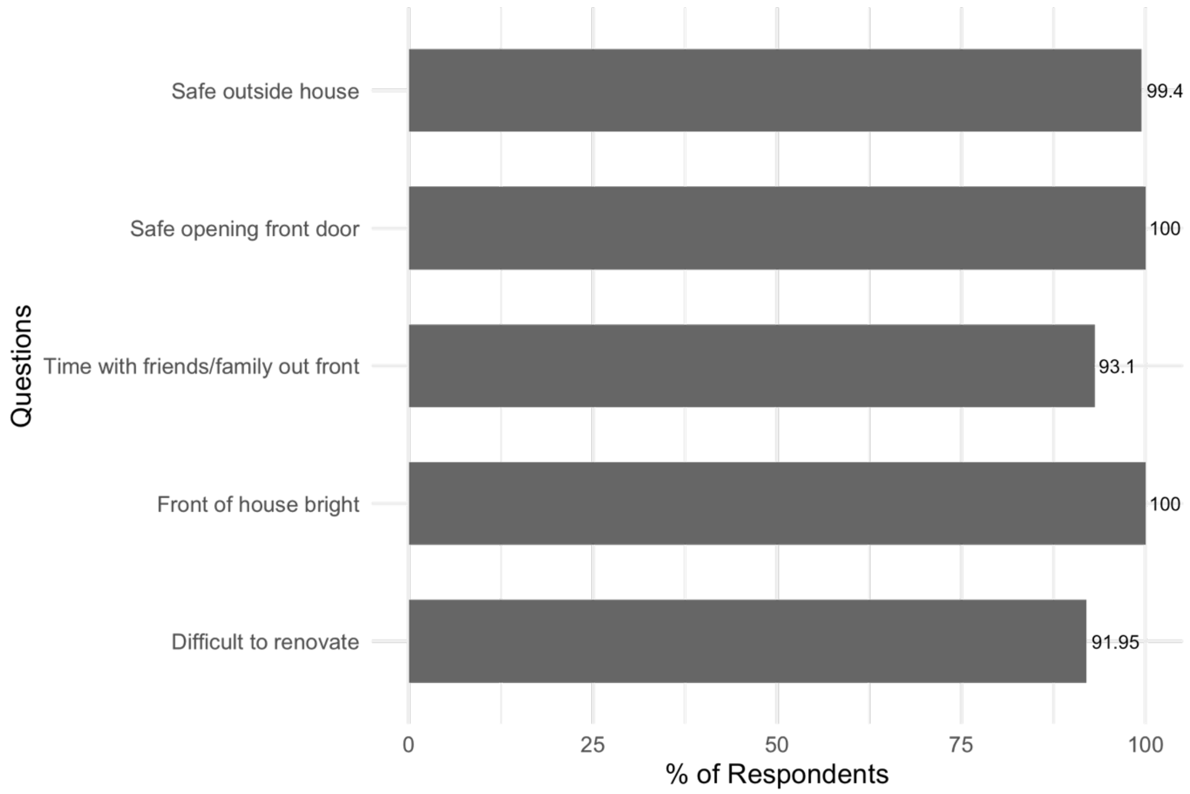


Figure 5. Opinions about the solar public light among the control group

Table 7. Willingness to pay for a replacement solar public light

	Pay 180 ZAR	Pay 370 ZAR	Pay 550 ZAR
	(1)	(2)	(3)
Treat (=1)	-0.006	-0.091	-0.016
	(0.068)	(0.089)	(0.070)
(Intercept)	0.631***	0.564***	0.366***
	(0.042)	(0.059)	(0.047)
Adj. R^2	-0.005	0.002	-0.004
Num. obs.	191	152	212
Clusters	113	96	106

Note: Standard errors clustered at the level of randomization. Each respondent was asked to consider whether they would be willing to pay for a replacement light if their light was stolen or vandalized, at one of three randomly shown price points: 180 ZAR, 370 ZAR, 550 ZAR. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 8. Heterogeneous effects: Gender

	Path Lit	Inf. Sett Lit	Safe Inf. Sett. Day	Safe Inf. Sett. Night	Safe Path Day	Safe Path Night	Risk of Burglary	Night Activity Index	Toilet at Night	Front House Night	Exp. of Crime Index	Burglary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A - Paths												
Treat (=1)	0.695***	0.061	0.092	0.091	0.114	0.101*	-0.065*	-0.258	-0.066	-0.016	0.083	0.035
	(0.065)	(0.070)	(0.077)	(0.055)	(0.071)	(0.054)	(0.034)	(0.345)	(0.073)	(0.068)	(0.115)	(0.050)
Female (=1)	0.069	-0.060	-0.042	-0.061	-0.016	-0.088**	0.005	-0.867***	-0.202***	-0.082	0.096	-0.004
	(0.042)	(0.059)	(0.063)	(0.039)	(0.064)	(0.036)	(0.020)	(0.303)	(0.061)	(0.052)	(0.093)	(0.036)
Treat*Female	-0.034	0.152*	0.022	-0.059	-0.054	0.008	0.039	0.443	0.025	-0.003	-0.208	-0.035
	(0.080)	(0.090)	(0.099)	(0.068)	(0.095)	(0.067)	(0.040)	(0.495)	(0.096)	(0.077)	(0.146)	(0.063)
(Intercept)	0.100***	0.276***	0.438***	0.162***	0.476***	0.152***	0.981***	5.162***	0.752***	0.305***	0.314***	0.076***
	(0.033)	(0.050)	(0.052)	(0.032)	(0.042)	(0.028)	(0.014)	(0.239)	(0.045)	(0.042)	(0.068)	(0.028)
Adj. R^2	0.455	0.024	0.005	0.016	0.002	0.029	0.013	0.019	0.034	0.002	-0.001	-0.004
Num. obs.	402	425	425	425	425	425	425	425	424	425	425	423
Clusters	112	112	112	112	112	112	112	112	112	112	112	112
Panel B - Compounds												
Treat (=1)	0.683***	-0.112	-0.206	-0.148	0.005	0.063	0.107	-0.771	-0.155	-0.189	-0.375**	-0.001
	(0.092)	(0.124)	(0.132)	(0.093)	(0.131)	(0.115)	(0.075)	(0.615)	(0.119)	(0.115)	(0.155)	(0.069)
Female (=1)	0.071	-0.192*	-0.257**	-0.107	-0.138	-0.046	0.141**	-0.598	-0.087	-0.208*	-0.134	0.055
	(0.095)	(0.113)	(0.123)	(0.079)	(0.114)	(0.097)	(0.062)	(0.487)	(0.117)	(0.112)	(0.173)	(0.075)
Treat*Female	-0.191	0.131	0.117	0.078	-0.057	-0.089	-0.165**	-0.217	-0.057	0.177	0.311	-0.031
	(0.119)	(0.151)	(0.155)	(0.097)	(0.141)	(0.122)	(0.076)	(0.759)	(0.151)	(0.139)	(0.222)	(0.100)
(Intercept)	0.174**	0.480***	0.680***	0.280***	0.600***	0.200**	0.840***	5.560***	0.760***	0.400***	0.480***	0.080
	(0.076)	(0.093)	(0.101)	(0.079)	(0.115)	(0.094)	(0.067)	(0.428)	(0.085)	(0.099)	(0.143)	(0.054)
Adj. R^2	0.323	0.000	0.031	0.006	0.008	-0.002	0.018	0.032	0.025	0.014	0.022	-0.014
Num. obs.	145	154	154	154	154	154	154	154	154	154	154	154
Clusters	49	50	50	50	50	50	50	50	50	50	50	50

Note: Standard errors clustered at the level of randomization. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 9. Heterogeneous effects: Distance from the nearest high-mast light

	Path Lit (1)	Inf. Sett Lit (2)	Safe Inf. Sett. Day (3)	Safe Inf. Sett. Night (4)	Safe Path Day (5)	Safe Path Night (6)	Risk of Burglary (7)	Night Activity Index (8)	Toilet at Night (9)	Front House Night (10)	Exp. of Crime Index (11)	Burglary (12)
Panel A - Paths												
Treat (=1)	0.549***	0.291**	-0.056	0.066	0.006	0.202**	-0.156***	1.026	0.086	0.196	-0.011	0.029
	(0.107)	(0.135)	(0.150)	(0.091)	(0.135)	(0.095)	(0.042)	(0.662)	(0.130)	(0.135)	(0.209)	(0.092)
Dist. to Nearest HML (m)	-0.000	0.003**	-0.002	-0.000	-0.002	0.001	-0.000	0.004	0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.005)	(0.001)	(0.001)	(0.002)	(0.001)
Treat*Nearest HML	0.001	-0.002	0.002	-0.000	0.001	-0.001	0.001***	-0.011*	-0.001	-0.002*	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.007)	(0.001)	(0.001)	(0.002)	(0.001)
(Intercept)	0.149**	0.030	0.542***	0.130**	0.600***	0.058	1.008***	4.335***	0.617***	0.163	0.253	0.062
	(0.075)	(0.080)	(0.114)	(0.060)	(0.109)	(0.049)	(0.010)	(0.417)	(0.089)	(0.099)	(0.178)	(0.067)
Adj. R^2	0.454	0.032	0.009	0.000	0.005	0.018	0.024	0.001	-0.001	0.001	-0.004	-0.006
Num. obs.	401	424	424	424	424	424	424	424	423	424	424	422
Clusters	112	112	112	112	112	112	112	112	112	112	112	112
Panel B - Compounds												
Treat (=1)	0.744***	0.450*	-0.139	0.101	0.105	0.237	-0.021	-0.438	-0.164	-0.268	-0.646**	-0.348**
	(0.171)	(0.257)	(0.263)	(0.181)	(0.290)	(0.201)	(0.104)	(0.965)	(0.230)	(0.162)	(0.251)	(0.141)
Dist. to Nearest HML (m)	0.003**	0.003	-0.001	0.001	-0.001	0.001	-0.000	-0.004	-0.001	-0.003***	-0.002	-0.002**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.006)	(0.002)	(0.001)	(0.002)	(0.001)
Treat*Nearest HML	-0.002	-0.005*	0.000	-0.002	-0.001	-0.002	0.000	-0.004	-0.000	0.002	0.005*	0.003*
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.010)	(0.002)	(0.002)	(0.003)	(0.002)
(Intercept)	-0.052	0.022	0.589***	0.159	0.558**	0.034	0.956***	5.503***	0.835***	0.542***	0.620***	0.277***
	(0.140)	(0.180)	(0.148)	(0.151)	(0.209)	(0.137)	(0.086)	(0.576)	(0.137)	(0.113)	(0.182)	(0.081)
Adj. R^2	0.336	0.020	-0.006	0.007	-0.013	-0.007	-0.019	0.016	0.022	0.022	0.025	0.020
Num. obs.	145	154	154	154	154	154	154	154	154	154	154	154
Clusters	49	50	50	50	50	50	50	50	50	50	50	50

Note: Standard errors clustered at the level of randomization. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 10. Local Average Treatment Effects

	Front House Lit	Path Lit	Inf. Sett Lit	Safety Index	Safety Index (Short)	Safe Inf. Sett. Day	Safe Inf. Sett. Night	Safe Path Day	Safe Path Night	Safe Inside Day	Safe Inside Night	Risk of Burglary	Risk of Vandalism
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A - Paths													
Endline Avg. Lux	0.055***	0.053***	0.012***	0.053**	0.017**	0.008**	0.005*	0.007	0.009***	0.003	0.006	-0.004**	0.000
	(0.007)	(0.007)	(0.004)	(0.025)	(0.008)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)
(Intercept)	0.087	0.021	0.215***	3.327***	1.071***	0.394***	0.116***	0.451***	0.082***	0.722***	0.429***	0.992***	0.917***
	(0.075)	(0.074)	(0.043)	(0.187)	(0.070)	(0.042)	(0.024)	(0.042)	(0.023)	(0.033)	(0.037)	(0.013)	(0.025)
First Stage Instrument													
Treatment	12.525***												
Robust St. Error	1.828												
F stat. for IV in First Stage	46.93***												
Adj. R^2	-0.081	-0.083	-0.034	-0.023	-0.027	-0.024	-0.005	-0.003	-0.009	-0.006	-0.003	-0.011	-0.003
Num. obs.	425	402	425	425	425	425	425	425	425	425	425	425	422
Clusters	112	112	112	112	112	112	112	112	112	112	112	112	112
Panel B - Compounds													
Endline Avg. Lux	0.047***	0.036***	-0.001	-0.001	-0.011	-0.006	-0.006	-0.000	0.002	0.001	0.006	-0.000	0.001
	(0.006)	(0.006)	(0.005)	(0.031)	(0.009)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)	(0.003)	(0.003)
(Intercept)	0.102	0.148*	0.352***	3.690***	1.334***	0.519***	0.219***	0.506***	0.166**	0.726***	0.377***	0.935***	0.893***
	(0.071)	(0.078)	(0.060)	(0.465)	(0.117)	(0.062)	(0.055)	(0.085)	(0.065)	(0.072)	(0.076)	(0.035)	(0.039)
First Stage Instrument													
Treatment	16.045***												
Robust St. Error	1.672												
F stat. for IV in First Stage	92.14***												
Adj. R^2	0.337	0.219	-0.009	-0.006	0.001	0.009	0.003	-0.007	-0.008	-0.008	-0.021	-0.007	-0.010
Num. obs.	154	145	154	154	154	154	154	154	154	154	154	154	152
Clusters	50	49	50	50	50	50	50	50	50	50	50	50	50

Note: Standard errors clustered at the level of randomization. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 10, Cont'd

	Night Activity Index	Night Act. Index (Short)	Toilet at Night	Friends/Family Night	Leave House Night	Front House Night	Leave House if Front Lit	Leave House if Inf. Sett. Lit	Exp. of Crime Index	Exp. Crime Index (Short)	Vandalism	Burglary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A - Paths												
Endline Avg. Lux	0.000	0.001	-0.004	0.000	0.000	-0.001	0.020***	0.010**	-0.003	-0.004	-0.002	0.001
	(0.017)	(0.010)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)	(0.001)	(0.002)
(Intercept)	4.667***	2.911***	0.647***	0.192***	0.352***	0.261***	0.121***	0.202***	0.375***	0.304***	0.045***	0.071***
	(0.160)	(0.095)	(0.036)	(0.027)	(0.039)	(0.032)	(0.042)	(0.036)	(0.058)	(0.044)	(0.017)	(0.020)
First Stage Instrument												
Treatment	12.525***											
Robust St. Error	1.828											
F stat. for IV in First Stage	46.93***											
Adj. R^2	-0.002	-0.002	0.002	-0.002	-0.002	-0.001	-0.013	-0.027	-0.005	-0.005	-0.016	0.001
Num. obs.	425	425	424	425	425	425	425	425	425	425	425	423
Clusters	112	112	112	112	112	112	112	112	112	112	112	112
Panel B - Compounds												
Endline Avg. Lux	-0.049**	-0.023*	-0.011*	-0.006	0.004	-0.004	0.010*	0.006	-0.012*	-0.011**	-0.002	-0.002
	(0.021)	(0.013)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.007)	(0.005)	(0.002)	(0.004)
(Intercept)	5.251***	3.137***	0.722***	0.259***	0.265***	0.268***	0.189***	0.236***	0.414***	0.293***	0.055*	0.120***
	(0.256)	(0.168)	(0.062)	(0.049)	(0.059)	(0.056)	(0.054)	(0.057)	(0.074)	(0.064)	(0.029)	(0.036)
First Stage Instrument												
Treatment	16.045***											
Robust St. Error	1.672											
F stat. for IV in First Stage	92.14***											
Adj. R^2	0.019	0.016	-0.046	0.024	-0.017	-0.022	0.019	-0.006	-0.034	-0.008	-0.014	-0.020
Num. obs.	154	154	154	154	154	154	154	154	154	154	153	154
Clusters	50	50	50	50	50	50	50	50	50	50	50	50

Note: Standard errors clustered at the level of randomization. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 11. "Border" group effects on endline outcomes of interest

	Average Lux	Front House Lit	Path Lit	Inf. Sett Lit	Safety Index	Safe Inf. Sett. Day	Safe Inf. Sett. Night	Safe Path Day	Safe Path Night	Risk of Burglary	Risk of Vandalism
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A - Paths											
Treat (=1)	13.321***	0.707***	0.702***	0.163***	0.699**	0.067	0.046	0.081	0.103**	-0.024	-0.013
	(1.715)	(0.042)	(0.043)	(0.057)	(0.326)	(0.054)	(0.040)	(0.060)	(0.041)	(0.022)	(0.044)
Border (=1)	5.870***	0.366***	0.333***	0.060	0.575	0.087	0.070	0.142**	0.128***	-0.041	0.034
	(1.166)	(0.072)	(0.068)	(0.051)	(0.379)	(0.068)	(0.050)	(0.067)	(0.043)	(0.027)	(0.035)
(Intercept)	2.132*	0.212***	0.135***	0.241***	3.389***	0.419***	0.123***	0.448***	0.089***	0.980***	0.916***
	(1.224)	(0.034)	(0.030)	(0.033)	(0.145)	(0.030)	(0.021)	(0.036)	(0.017)	(0.011)	(0.024)
Adj. R^2	0.347	0.388	0.390	0.020	0.011	0.001	0.002	0.008	0.021	0.003	-0.001
Num. obs.	422	422	399	422	422	422	422	422	422	422	419
Clusters	112	112	112	112	112	112	112	112	112	112	112
Panel B - Compounds											
Treat (=1)	15.459***	0.716***	0.610***	-0.045	-0.391	-0.160	-0.098	-0.059	0.003	0.032	-0.022
	(1.666)	(0.076)	(0.081)	(0.093)	(0.581)	(0.100)	(0.068)	(0.113)	(0.089)	(0.047)	(0.046)
Border (=1)	10.093***	0.372**	0.270**	-0.043	-0.479	-0.063	-0.070	-0.004	-0.082	0.025	0.025
	(3.671)	(0.151)	(0.134)	(0.085)	(0.644)	(0.105)	(0.075)	(0.108)	(0.087)	(0.070)	(0.041)
(Intercept)	1.852*	0.217***	0.214***	0.367***	3.950***	0.533***	0.217***	0.533***	0.200***	0.917***	0.917***
	(0.927)	(0.064)	(0.071)	(0.052)	(0.491)	(0.066)	(0.055)	(0.091)	(0.071)	(0.039)	(0.031)
Adj. R^2	0.458	0.400	0.283	-0.011	-0.007	0.007	0.001	-0.010	-0.005	-0.010	-0.010
Num. obs.	153	153	144	153	153	153	153	153	153	153	151
Clusters	50	50	49	50	50	50	50	50	50	50	50

Note: Standard errors clustered at the level of randomization. The reference category is the control group. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 11, Cont'd.

	Night Activity Index	Toilet at Night	Friends/Family Night	Leave House Night	Front House Night	Leave House if Front Lit	Leave House if Inf. Sett. Lit	Exp. of Crime Index	Vandalism	Burglary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A - Paths										
Treat (=1)	0.164	-0.080	0.014	0.001	-0.006	0.237***	0.134**	-0.034	-0.027*	0.026
	(0.242)	(0.057)	(0.040)	(0.048)	(0.048)	(0.047)	(0.055)	(0.079)	(0.016)	(0.030)
Border (=1)	0.013	0.012	-0.035	0.041	-0.027	0.158**	0.113*	-0.003	0.038	0.032
	(0.276)	(0.050)	(0.045)	(0.060)	(0.053)	(0.061)	(0.060)	(0.103)	(0.033)	(0.039)
(Intercept)	4.601***	0.639***	0.192***	0.345***	0.256***	0.167***	0.212***	0.365***	0.034**	0.064***
	(0.146)	(0.032)	(0.023)	(0.035)	(0.028)	(0.025)	(0.028)	(0.054)	(0.014)	(0.019)
Adj. R^2	-0.004	0.002	-0.003	-0.004	-0.004	0.053	0.015	-0.004	0.011	-0.002
Num. obs.	422	421	422	422	422	422	422	422	422	420
Clusters	112	112	112	112	112	112	112	112	112	112
Panel B - Compounds										
Treat (=1)	-0.807**	-0.157	-0.131*	0.072	-0.006	0.206**	0.106	-0.247*	-0.049	-0.032
	(0.399)	(0.101)	(0.076)	(0.088)	(0.048)	(0.086)	(0.083)	(0.125)	(0.036)	(0.076)
Border (=1)	-1.220***	-0.187*	-0.166**	0.057	-0.027	0.081	0.090	-0.198	-0.037	-0.075
	(0.331)	(0.094)	(0.074)	(0.096)	(0.053)	(0.085)	(0.085)	(0.127)	(0.042)	(0.051)
(Intercept)	5.367***	0.717***	0.283***	0.267***	0.256***	0.183***	0.233***	0.433***	0.067**	0.133***
	(0.256)	(0.056)	(0.049)	(0.061)	(0.028)	(0.050)	(0.058)	(0.079)	(0.032)	(0.037)
Adj. R^2	0.032	0.016	0.019	-0.008	-0.004	0.029	-0.002	0.021	0.000	-0.005
Num. obs.	153	153	153	153	422	153	153	153	152	153
Clusters	50	50	50	50	112	50	50	50	50	50

Note: Standard errors clustered at the level of randomization. The reference category is the control group. ***p < 0.01; **p < 0.05; *p < 0.1.

CONCLUSION

This dissertation demonstrates that focusing on life at night in informal settlements has important implications for how academics and policymakers think about access to critical public infrastructure in these neighborhoods, not to mention basic quality of life and human dignity. In this section, I will summarize the main findings of each of the four articles, contend with the limitations in this work, explain the key lessons for public policy, and discuss the two broader academic contributions of this thesis. I will close with some reflections on where future research on life at night in informal settlements might go from here.

REVIEW OF MAIN FINDINGS

Articles 1 and 2 both explore nighttime pedestrian activity in informal settlements from a diverse set of perspectives. Article 1 primarily speaks to the urban planning literature, however, the use of sensors for social science research is also relevant to the field of development engineering. My co-authors and I use pedestrian motion sensor data gathered between October 1 – November 30, 2019 to better understand nighttime movement patterns in the informal settlement we study. We find that average motion in the mornings and evenings is quite different, suggesting residents engage in very different types of activities at different times of day. With this highly granular data we test whether existing theories of pedestrian activity — route optimization and space syntax, developed primarily in high-income, formal cities — predict the patterns we observe. We find that the shortest paths calculation (route optimization) is correlated with average observed pedestrian activity during the evenings (6:00 – 9:00 pm) as well as on weekdays and weekends, but not during early morning hours (5:00 – 8:00 am). We also find that the space syntax measure of choice does not correlate with the pedestrian motion measurements, indicating that the dynamics of informal settlements may complicate the predictive ability of this theory-driven measure. Finally, we find that the performance of both theory-driven calculations varies by time of day, opening up questions about how movement patterns in informal settlements may differ from patterns observed in formal areas over the course of an average day.

Article 2 starts with a question at the intersection of public health, development economics, and urban planning: given the constraints that define life in informal settlements, can residents of informal settlements comply with lockdowns of public and economic life to limit the spread of COVID-19? Using pedestrian motion sensor data collected between February 14, 2020 and June 18, 2020, we analyze how nighttime pedestrian activity during the evening, early morning, and nights changes in response to the strict lockdown in South Africa, as well as in response to increasing awareness of COVID-19 prior to the lockdown and the loosening of measures in the two months after the initial lockdown. We find that pedestrian activity already began declining in March prior to the start of lockdown by 23% in paths and 19% in compounds (semi-private cul-de-sacs). The decline in paths in March is roughly half the overall activity decline we document. Once the first lockdown began on March 27, 2020 pedestrian activity in paths decreased by 48% and by 61% in compounds compared to activity measured in February 2020. Weekends and the hours between 6:00 – 9:00 pm and 6:00 – 8:00 am demonstrate the biggest changes, suggesting that leisure times and typical commuting times were heavily impacted. Yet, the commute hours continue to have the highest levels of activity, indicating that at least some people were still commuting despite the economic shutdown. Our results show that mobility reduction is large, however, the reductions are still smaller on average than those documented in high-income countries. We conclude that residents of informal settlements do comply with state-mandated lockdowns to the best of their ability given the circumstances of informal settlements that make it difficult. That said, we also find that awareness of COVID-19, when far less strict regulations were in place prior to the first lockdown, also led to mobility declines.

Public lighting and its influence on various aspects of life at night is the main focus of Articles 3 and 4. These two articles, which build on each other, describe results that are important for the development economics literature, but also address key questions about public lighting and urban infrastructure interventions in urban planning, criminology, and lighting engineering. In Article 3, I assess the pre-existing lighting situation in the informal settlement that is the study site for this entire dissertation, which is lit by two high-mast lights located on the periphery of the neighborhood. Using light measurements collected by residents, I find that average lux levels are low in the settlement overall and that light is not uniformly distributed. These findings indicate that even though this informal settlement officially has access to public lighting, which is not true for all informal settlements, the quality of the light is poor.

Given these low light levels, I then combine the light measurements with household survey data to analyze how the lighting situation influences perceptions of safety, perceived risk of crime, and willingness to engage in public space at night. I find that there is only a relationship between light levels and respondents' perception of safety at night on the brightest paths. These paths have lux values of 10 lux or more, which is a higher threshold than most of the optimal lighting thresholds discussed in the literature. I find no relationship between light levels and perceived risk of crime or willingness to engage in public space at night. I also replace light levels with distance from the nearest high-mast light as the predictor of interest, since this is a possible proxy when light measurements are not possible. I find results only differ slightly, indicating that this measure could be useful for studying larger numbers of informal settlements. These findings suggest that uneven lighting limits the positive benefits of public lighting even for residents living close to the high-mast lights and on the brightest paths because the rest of the neighborhood is not well lit. These results support the existing literature emphasizing the importance of uniform light. Furthermore, this research contributes to the understanding of effective public lighting technologies for informal settlements and is important for planners seeking to design development initiatives for these neighborhoods.

Article 4 is an impact evaluation assessing the efficacy and impact of wall-mounted solar public lighting on many of the same aspects of life at night that are explored in Article 3, though we also include experience of crime as an outcome. We find that solar public lights are effective at improving the light situation in the informal settlement — we measure a six-fold increase in average lux on treated paths and an eight-fold increase in treated compounds. These strong effects are at least partially due to the fact that we documented far less theft and vandalism than most stakeholders in the project, including residents, expected. In total, seven lights were vandalized and six were stolen during the six-month study intervention.

We also find the treatment had a significant effect on perceptions of safety among residents living in paths, especially in the paths where they live at night, but it had no impact on residents living in compounds. This finding is generally consistent with the existing observational literature that finds a relationship between lighting and safety. In our study, though, increased perception of safety does not translate to greater engagement in public space at night. We find no effect of the treatment on nighttime activities, in general, in paths and, if anything, nighttime activity decreases in compounds. We do, however, find that respondents in both treatment groups are more likely to use shared sanitation at night compared to baseline. Although this appears to be an indication of spillover, we find that spillover effects are not widespread as activity between baseline and endline declines for other nighttime activities. We also find no indication of systematic spillover when we look at households living immediately adjacent to paths or compounds of the opposite treatment status. One reason why we may see so little change in nighttime activities is the rise in gang activity in this area, particularly demands for "protection money," which discourage people from leaving their homes no matter how much light there is. Another reason could be related to the ongoing COVID-19 pandemic. Finally, we find no effect on experience of crime, which was expected given the relatively small size of our study and the fact that crime is a rare phenomenon even in a high-crime area.

Taken together, the findings from these two articles indicate that in this informal settlement high levels of brightness do influence perception of safety. Yet, given that neither article includes a scenario where bright lighting is uniformly distributed (e.g., all structures have a solar public light) it is unclear whether the effects on safety would be larger (as the literature suggests) and whether it might be possible to learn more about the link between light and nighttime behavior.

LIMITATIONS

A few limitations should be considered in evaluating this study of nighttime life and public lighting in informal settlements. From the perspective of development economics, in particular, the first limitation to mention is external validity. While it is a well-known critique of RCT's that it is difficult to demonstrate that the findings are externally valid beyond a certain area, that is a particular problem in this thesis because it is focused on a single informal settlement. The decision to undertake the project was made with full cognizance of this limitation. We determined that the research was worthwhile, despite concerns about external validity, since the topics have received almost no attention in the academic literature. To put it plainly, we had to start somewhere.

In addition, as discussed in the Introduction, focusing on one informal settlement enabled the sort of novel nighttime data collection approaches we were able to attempt. It would also have been cost prohibitive, and imprudent, to provide free solar public lights to a large number of informal settlements without established evidence that they are a feasible technology solution for that context and without practice-based awareness of unintended consequences.

Challenges with the pedestrian motion sensors presented several limitations to the research. First, the sensors were initially designed to measure activity during all hours of the day. After piloting the sensors in a different informal settlement, we concluded that the sensors were capable of this functionality, however, when we deployed the final sensors on site, we quickly noticed erratic data during daytime hours. By conducting manual counts both in the field and at ETH Zurich, we were able to determine that something about the interaction between sunlight and the local building materials prompted the sensor to record impossibly high numbers of triggers. By comparing manual counts to the sensor data, we were able to determine the set of hours during which the sensors recorded reliable data. Although this problem with the sensors still allowed us to study nighttime life, the primary focus, without daytime data our understanding of how night differs from day is limited. The implications of this limitation are clear in Articles 1 and 2. In Article 1, we compare our observed data to theories that predict pedestrian flows. Yet, the majority of the literature that has also sought to compare these theoretical predictions to pedestrian activity has conducted counts during daytime, rather than nighttime hours. In Article 2, we document declines in nighttime activity in response to COVID-19 awareness and stringent lockdown restrictions, however, we cannot say how much of that decline is due to activity that has been shifted to daytime hours.

The research was also limited by theft and vandalism of the pedestrian sensors. There were concerns about this problem from the early stages of development, at least partially driven by worries that thieves would be interested in the materials inside the sensors. As a result, the sensors were designed with thick plastic casing (not valuable) and Sensen made efforts to limit the materials inside that might be reusable in other venues. Initially, though, most of the theft and damage was reportedly driven by outsiders who came into the informal settlement and believed the sensors were cameras. Community members knew that they were not cameras due to community meetings and widespread communication, but unfortunately it was very difficult to account for visitors. Still, theft and vandalism remained somewhat minimal early on, hence why we have sufficient data for Articles 1 and 2. That said, our smaller sample of sensors limited our ability to include the sensor data in Article 3.

Unfortunately, sometime in late May 2020 someone organized a group of children to steal as many SD storage cards from the sensors as possible. They stole about 60 of the 171 total sensors that were installed at the time before a data collector caught them. Since the lighting project was on hold due to the COVID-19 pandemic, we decided to remove all of the sensors and reinstall them when the lighting intervention began so that we could still collect data on how path usage changed in response to the lights. With far fewer sensors, we could only install the remaining sensors in path segments, not compounds. Still, less than two weeks after the sensors were reinstalled in late October, another round of theft essentially ended the sensor data collection. As a result, we are not able to analyze how pedestrian activity changed in response to the solar lighting, which is a significant limitation as this was one of our main questions early on in the project.

Another limitation is the challenges that interdisciplinary and transdisciplinary research can present to unbiased estimates based on self-reported outcomes. This limitation is also linked to the disadvantage of working in a single settlement. The level of engagement with the community, particularly researcher presence, required to implement this project justifiably raises questions about priming. However, the level of data collection and relationship building required to ensure that the community would accept the lighting intervention made this level of interaction unavoidable and highly beneficial to the project in other ways (see Introduction). In addition, throughout the project S. Briers was simultaneously conducting qualitative research in the same area about the same project, therefore there were constant discussions about how to limit priming for both researchers. While other RCT's implement procedures like double blinding, nothing even remotely similar was possible in this field-based RCT. Instead, we took several steps to minimize priming. First, during baseline, we limited the number of questions we asked about public lighting so as not to raise expectations and influence responses to questions. Second, the qualitative baseline was primarily conducted after the baseline household survey had been administered so that respondents would not be unduly influenced by qualitative interviews. Unfortunately, this procedure was not possible at endline due to delays caused by COVID-19 and the administrative constraints of graduation requirements. Instead, the qualitative and quantitative endlines were spaced by nearly two months to reduce the likelihood of any potential priming.

Finally, the delays caused by the COVID-19 pandemic heavily limited the timeline of the project. For nearly two months, no fieldwork could be done due to the strict lockdown imposed on March 27, 2020. The slow re-opening of the South African economy and the fact that all field staff were residents of the informal settlement made it possible to slowly resume data collection. Ultimately, due to these delays and other delays linked to the delivery of the lights, we ultimately shortened the intervention time period to six months, down from an original plan of one year. In particular, this limited our study of crime experiences, as more data might have increased the chances of detecting an effect if one existed. In addition to the timeline, anecdotally, the pandemic appeared to lead to a lot of turnover in the informal settlement, based on the impressions of the leadership. Therefore, in the absence of the pandemic, we might have been able to speak to more of the same respondents who were interviewed at baseline.

PUBLIC POLICY LESSONS

In line with the missions of both the ISTP and DEC, this dissertation was designed with the goal of policy-relevant insights, as well as academic contributions. Furthermore, the applied nature of the research and the effort to conduct that research in both an interdisciplinary and transdisciplinary way means that the project was well set up to produce lessons that could be used to guide informal settlement policy. Based on the main findings and conclusions discussed above, I make the following policy recommendations targeted broadly at both international development organizations as well as local governments.

The first recommendation is for a broader range of actors to commit to mapping informal settlements. As Article 1 indicates, so long as informal settlements continue to exist as unplanned neighborhoods within or adjacent to formal ones, the nature of activity inside them may be quite different than activity in formal areas. Article 2 makes clear one present and urgent application of this knowledge: disease prevention and management. Understanding pedestrian activity in informal settlements could also guide more effective infrastructure interventions and better placement of infrastructure to enhance access and, with regard to public health, hygiene. Yet, without any attention or even any comprehensive attempt at mapping these areas (e.g., in Google maps), there is no way to know what more is possible. For cities that fear mapping will legitimize neighborhoods they view as illegal encroachments, it is important to say that mapping does not confer tenure security and these people exist and influence the city, whether they are documented or not. COVID-19 also made apparent that the costs of ignoring these neighborhoods may be higher than expected, since a place that is unmapped is difficult to target with public health services designed to prevent the spread of infection to all members of the population.

The second contribution to the policy debate is the experimental evidence presented in Article 4 that public lighting leads to a small, but significant increase in perceptions of safety at night in informal settlements, neighborhoods which are particularly affected by high crime rates, especially in South Africa (Brown-Luthango et al., 2017; Matzopoulos et al., 2020; UN-Habitat, 2007, 2011). As Chalfin et al. (2021) point out to motivate their own lighting experiment, the paucity of conclusive evidence proving that public lighting has the benefits we intuitively expect from it prompted a 1997 National Institute of Justice report to the U.S. Congress to conclude that *"we can have very little confidence that improved lighting prevents crime*." While this research could not answer the question of whether public lighting decreases crime in informal settlements, the fact that people feel safer is itself important for quality of life. In a UN report to the General Assembly a Special Rapporteur wrote, "It is a human rights imperative that informal settlements be upgraded to meet basic standards of human dignity" (UN, 2018).

Public lighting infrastructure has often been neglected in these neighborhoods due to a focus on more visible "daytime infrastructure," like water and sanitation, but our findings suggest that better lighting will improve nighttime visibility and perceptions of safety, not to mention the potential for longer-term positive benefits that we are unable to test with our study. Importantly, while it is hard to quantify the monetary value of feeling safer where you live, the fact that 60% of residents would be willing to pay some amount of money for solar public lights is an indicator that policymakers and the international development community should take note of — residents of informal settlements want security. Furthermore, we find evidence that public lighting enhances access to shared sanitation, thereby offering a multiplier effect in terms of access to infrastructure. Thus, these results suggest that more and evenly distributed light, however it is provided, can improve urban quality of life in low- and middle-income countries, an imperative of SDG 11 (United Nations, 2021). Public lighting, therefore, should not be an afterthought, but rather be included in the infrastructure targets defined by the SDGs as well as in local goals to expand access to public infrastructure in informal settlements. Furthermore, greater study of nighttime life in general is essential to understand whether the SDG 11 goals to "make cities and human settlements inclusive, safe, resilient and sustainable" are comprehensively met (United Nations, 2021).

The third recommendation is related to the strong effects we find on the efficacy of solar public lights — an approximately six-fold increase in average path-level lux. This finding provides critical evidence of a viable lighting solution for grid-connected and possibly also off-grid informal settlements. The results are also an indicator of what impacts can be realized at the level of brightness these lights provide. The findings from this project also underscore the inadequacy of high-mast lighting in informal settlements, which demonstrably does not provide sufficient light. For policymakers, the takeaway is not necessarily that solar public lights are the only answer — we can in no way confirm that — but rather that there is a need for lighting standards to guide public lighting design for informal settlements in order to ensure that public lighting provision in informal settlements is not just symbolic, but also effective.

With regard to specifically recommending solar public lights, it is important to be clear about the advantages and disadvantages of such a solution, while acknowledging that no technology is perfect. In comparison to high-mast lights and standard streetlights, wall-mounted solar public lights have several advantages in informal settlements. First, because they are solar-powered they are not vulnerable to grid unreliability, a major problem in Cape Town as well as many other cities with large numbers of informal settlements. Second, they can be considered "temporary" infrastructure in that they are moveable. This quality has benefits for city governments that are constrained by property laws from installing "permanent" infrastructure in informal settlements. Furthermore, at endline, we learned that more than 40% of respondents reported renovating their structure in the previous 12 months and during the intervention 22 households asked for help removing the solar system to enable a renovation. While renovations could be a challenge to scale up, since they will raise maintenance costs, they are a reality of life in informal settlements and the solar lights can be easily and safely removed with a small amount of know-how. Third, since the lights are wall-mounted they do not take up scarce and valuable space in paths or compounds and do not require forced evictions to enable installation, unlike high-mast lights and possibly also standard streetlights. Fourth, we discuss back-of-the envelope calculations in Article 4 that suggest that solar public lights may be cost-competitive with high-mast lights, at least on the basis of up-front costs. If we include the installation and maintenance costs, we arrive at a cost of roughly US $70 per structure, which is very close to the per structure estimate we arrived at for high-mast lights based on 2019/2020 budget for public lighting (City of Cape Town, 2019a), except that we clearly document the solar public lights provide more lighting than the high-mast lights. Therefore, there is a high likelihood that this situation is financially feasible in the City of Cape Town and may also be a better alternative in other cities considering emulating South Africa's use of high-mast lights. Finally, the fact that the solution we study is solar-powered means it would also fit within the climate resilience goal of many cities, including Cape Town, to expand the use of renewable energy (City of Cape Town, 2019b).

The lights also have some limitations that are similarly important for policymakers to consider. Solar-powered lights rely on a battery for storage, which typically come with warranties between one and three years. As the batteries make up a substantial share of the cost of the system, especially when purchased separate from the casing, these lights will require a major component to be replaced more often than a more traditional piece of lighting infrastructure. In addition, the lights are not only vulnerable to routine issues, like house renovations, but also to unfortunately common disasters like fires. For example, a fire in the informal settlement we studied burned 22 houses to the ground and also destroyed the solar lights installed there. By testing a hybrid service provision model, which draws on the skills and capabilities of local residents, we have been able to show that although solar public lights present different challenges as compared to high-mast lights, maintenance options exist. The City of Cape Town, for example, already participates in the South African Expanded Public Works Programme (EPWP), which provides temporary employment to local residents to maintain public infrastructure.[77] The maintenance model we used in the study was inspired by this program, therefore a citywide solar public lighting program for informal settlements could already quickly be adopted by the City of Cape Town, as well as other South African cities.

To some extent, this last recommendation may be in the process of being realized. In December 2020, the City of Cape Town's Sustainable Energy Markets Department put out a request for information (RFI) entitled "Innovative Public Lighting Solutions for Informal Settlements with no grid access." S. Briers and I, along with our local light engineering partner Keyaam DuToit, responded to the call and our response was selected for follow-up in March 2021. Since then, we have maintained an open line of communication with the Sustainable Energy Markets Department and organized a site visit for them in October 2021. Shortly after, we also presented several of the results discussed in Articles 3 and 4 to this same department as well as to the City

[77] More information about the City of Cape Town's EPWP is available here: http://www.capetown.gov.za/work%20and%20business/jobs-and-skills-development/youth-careers/find-an-opportunity-with-epwp

of Cape Town's Urban Catalytic Investment Group. At the time of this writing, a discussion is ongoing between the research team and both groups at the City of Cape Town on how to move forward with a city-supported pilot project.

BROADER ACADEMIC CONTRIBUTIONS

Beyond the contributions mentioned in each of the articles, this thesis also makes two broader contributions to the academic arena, which I will discuss in this section.

PUBLIC LIGHTING DECENTRALIZED: THE IRONY OF INFRASTRUCTURE ACCESS IN INFORMAL SETTLEMENTS

The first broad contribution to the academic literature on infrastructure access in informal settlement is the exploration of a highly decentralized approach to providing public lighting. The irony of the approach studied in Article 4 is that the solar public lights are installed on private homes, while typically private infrastructure such as toilets, water taps, and even waste collection are public, shared, and far more centralized. In one sense, it flies in the face of the more typical approach to infrastructure provision in informal settlement, but in another sense, it fits a pattern in which the approach is the opposite of what is provided in formal urban areas.

At the heart of this irony sits a debate that is addressed in different ways in different fields: centralized versus decentralized infrastructure, or in more theoretical terms, technocratic, top-down approaches to infrastructure provision versus a more grass-roots, bottom-up framework. In their paper elucidating this debate, Pritchett and Woolcock (2004) describe these two sides as follows. On the technocratic side, infrastructure provision (broadly speaking) is guided by a "standard organization algorithm which defines "*need* as the problem, *supply* as the solution, *civil service* as the instrument." While the grass-roots, decentralization side, they say, is defined "by terms such as 'empowerment,' 'participation,' 'accountability,' 'transparency,' or 'good governance'" and an emphasis on "institutional heterogeneity." As they see it, the fundamental critique of the former is that "one size does not fit all," while the major critique of the latter is that " 'any size fits any' or 'anything goes'" is also unlikely to be sufficient for successful development. So-called participatory approaches (their shorthand) might even lead to further or entrenched marginalization of the poor.

Translating this debate to the specific question of wall-mounted public lighting in informal settlements highlights why this discussion spurs so much tension across academic disciplines. When S. Briers first presented the concept for wall-mounted public lights (the presentation which sparked the project), one of the key arguments was that they are an example of human-scale infrastructure, while high-mast lights, which loom over informal settlements, are decidedly not. When we began collaborating, this argument morphed into the explicit goal to source a light that could address the specific characteristics of informal settlements in Cape Town. Out of this motive, which sits in the "participatory" camp, came a) the idea to install the lights over front doors to promote individual ownership and responsibility for the light even though it leaves paths without front doors dark; and b) the idea to use solar-powered lights rather than lights that plug into household electricity, since grid reliability is a constant issue and residents of informal settlements need lighting to safely access shared infrastructure. On the other hand, city government, in this case, the City of Cape Town, was always envisioned as the service provider, albeit via employment of local people to manage the transaction-intensive aspect of maintaining lights on individual homes. The reason was that public lighting is a public service. In our view, privatizing the delivery of public lighting or outsourcing it entirely to NGO's would realize the fears of those who criticize the grass-roots, participatory approach for marginalizing the poor because the city would no longer be held accountable for a service it is responsible for providing in formal areas.

Pritchett and Woolcock (2004) broadly define public services as either discretionary or not (i.e., requiring granular decision making or not) and either transaction intensive or not (i.e., requiring frequent contact with beneficiaries or not). Standard public lighting would most typically be considered non-discretionary, as a minimal amount of information is needed to make decisions and those decisions are often governed by technical guidelines, and transaction-intensive, as civil servants must install and maintain each individual light, which can amount to hundreds of thousands. As a result, standard public lighting is what the authors would consider a program.

The solar public lighting approach studied in this thesis changes this dynamic, creating a service that is both discretionary and transaction-intensive. Pritchett and Woolcock (2004) argue that this makes solar public lighting a "practice," which "provide[s] the biggest headache… because [it is] intrinsically incompatible with the logic and imperatives of large-scale, routinized, administrative control." The second two articles in this thesis, thus, implicitly raise the question of whether cities should continue with the more or less top-down programmatic approach to public service provision in informal settlements, or whether cities need to rethink how they engage with public infrastructure decisions in informal settlements. The former tends to underly decisions like placing public infrastructure (e.g., sanitation and water taps) on the perimeter of informal settlements where it is most accessible by service vehicles, while the latter could prioritize serving the needs of the residents rather than creating convenience for the service provider. Although this project could not demonstrate whether a "practice" model would work at scale, there is some experimental evidence that some of the core tenets of the approach have been effective in Bolivian small infrastructure projects, though the study does not focus on informal settlements (Yanez-Pagans & Machicado-Salas, 2014). Thus, this thesis provides the impetus for further exploration of the sustainability of such a public service delivery model in informal settlements.

DATA COLLECTION IN INFORMAL SETTLEMENTS: LESSONS FOR DEVELOPMENT ECONOMISTS AND DEVELOPMENT ENGINEERS

Collecting data in informal settlements is notoriously difficult, as evidenced by the proliferation of efforts to use satellite imagery to extract information about these neighborhoods without needing to physically go to one.[78] To gather the sort of detailed data necessary for the articles presented in this dissertation required some creative approaches since at least two types of data collection have not been attempted in other informal settlements: pedestrian motion sensor data and lux measurements.

Data collection is where the value of transdisciplinary research was truly evident in this project. As discussed in the Introduction, although we had many problems with the pedestrian motion sensors towards the end of the study, the residents of the informal settlement who served as data collectors played a critical role in making the pedestrian motion sensors work as well as they did. Similarly, the lux measurements represent a novel dataset and they would not have been possible to collect without direct involvement of the local data collection team. Data collectors received detailed training and checked in with me every day, but they also proposed numerous changes to methods, since they directly experienced the challenges, and also came up with their own techniques for staying organized in the field and staying safe. It is important to emphasize that this engagement was not just for the sake of conducting participatory research as a matter of principle, but it was also essential. That is an important takeaway for other researchers seeking to advance quantitative research in informal settlements.

The other major type of data collected for this research was household survey data. While household survey data is far from a novel data collection approach, the process still revealed some important lessons that bear underscoring. Practically by definition, informal settlements are a relatively fractured sub-category of urban area and the surveys conducted in them reflect this. Despite the efforts of organizations like Slum Dwellers International (SDI)[79], which has led community-based mapping and data collection efforts in informal settlements all over the world, there are no comprehensive databases containing detailed information about residents of informal settlements that could, for example, be harmonized for either larger, comparative studies or longer-term panel analyses. Yet, there are efforts underway to build something like this that researchers can contribute to.

For example, in the Western Cape, the province which encompasses Khayelitsha (as well as the rest of the City of Cape Town), the provincial government provides guidance on conducting what are known as informal settlement enumerations.[80] In order to make the baseline survey a more broadly useful dataset, we combined our research goals with the community's interest in

[78] One example is the Frontier Development Lab project, "Mapping Informal Settlements in Developing Countries using Machine Learning with Noisy Annotations and Multi-resolution Multi-spectral Data." More information available here: https://frontierdevelopmentlab.github.io/informal-settlements/; A discussion of various efforts is available here: https://venturesafrica.com/how-artificial-intelligence-is-being-used-to-map-african-cities-to-improve-services-and-infrastructure/

[79] Slum Dwellers International is an organization focused on community-driven mapping and data collection in informal settlements: https://sdinet.org/explore-our-data/

[80] This effort is part of the Western Cape's Informal Settlement Support Programme. More information is available here: https://www.westerncape.gov.za/your_gov/70/documents/reports_research/I/48163?toc_page=1

an enumeration. Using the Western Cape's guidelines, we included the most essential questions for an informal settlement enumeration, keeping the wording as similar as possible to ensure that harmonization with other informal settlement enumerations conducted by other organizations might eventually be possible. Once the data was cleaned and we received permission from the informal settlement's leadership, we also shared the enumeration dataset with the City of Cape Town's Data Science Unit, which is working to build out a database for both inter-departmental use (e.g., upgrading and disaster relief) as well as research purposes. Engaging in these ongoing efforts by both the Western Cape and the City of Cape Town to improve data collection and dissemination processes in informal settlements hopefully enables the intensive household survey effort to have a reach beyond this project.

The detailed map of the structures and path network in the informal settlement enabled all three data collection efforts discussed in this section. While some organizations, like SDI, focus primarily on mapping the boundaries of informal settlements to make them visible to local governments (Beukes, 2015), the lesson learned from this project is that more detailed mapping of the informal settlement path network can provide the bedrock for the kind of quantitative research, e.g., randomized controlled trials, that are relatively common in rural areas, but rare in informal urban areas. In the end, nearly every aspect of this project from sensor placement, light measurements, household surveys, randomization, installation tracking, etc. hinged on the map. The first draft of the map of this informal settlement was created in collaboration with S. Briers as well as two leaders of the informal settlement, Xolelwa Maha and Thabisa Mfubesi. Using a February 2018 satellite image of the area publicly available on the City of Cape Town Open Data Portal[81] as a reference, we traversed the entire informal settlement marking the paths, compounds, and dead ends as well as key infrastructure. This process took about the three days. Then, prior to the baseline survey, based on guidance from a local NGO called Violence Prevention through Urban Upgrading (VPUU), we developed a house numbering system with the community leadership and worked with them to number each building. Using Open Street Maps on our phones, we simultaneously mapped the shape of each house and labelled it with its new number, marked the location of the doors, and recorded some additional details about each plot. This process also took a little less than a week. Therefore, in less than two weeks it was possible to build a tool that enabled every phase of the project. At the same time, the mapping process also helped build trust between the research team and the leadership and provided the leadership with a detailed overview of their community, known benefits of informal settlement mapping (Garau et al., 2005). Other academics could easily replicate this process to expand opportunities for research in informal settlements.

[81] City of Cape Town Open Data Portal: https://odp.capetown.gov.za

CLOSING

The overarching conclusion that can be drawn from this research is that effectively designing urban infrastructure upgrading in informal settlements, and achieving SDG 11, is not truly possible without studying life at night in these neighborhoods. I would like to conclude this dissertation with some thoughts on future research going forward.

First, as mentioned in the Introduction, there is no documentation of how many informal settlements have public lighting and how many do not. While the fact that informal settlements expand and new ones emerge all the time makes such an accounting difficult, it seems, as far as I can tell that it has not yet been attempted. There is an opportunity to combine nighttime lights satellite imagery with other secondary data sources and on the ground verification to improve our knowledge about access to this public service. As anyone who has read a report on rural electrification or access to water and sanitation knows, understanding the sheer scale of the challenge motivates both academic and policy interest, which are currently in short supply.

Second, there is an opening for lighting engineers to collaborate with development economists or urban planners to develop the lighting standards or guidelines I recommend through additional research in more informal settlements in different countries. Standards make it harder for policymakers to sideline infrastructure because the information exists to guide implementation. In other words, it removes the burden on individual cities to reinvent the wheel. For example, the World Bank's Lighting Africa program[82] created quality standards for household solar task lights. These standards intended to make it possible for consumers to source high quality solar products as well as help government's define regulations to support local markets for indoor solar lights. While this initiative is not precisely translatable to public lighting, the spirit of easing the process of making a technology decision through the definition of standards is similar. Such a program could provide a rough model for creating a similar set of guidelines for public lighting in informal settlements.

Third, as discussed, the findings presented here are limited by the fact that they are based on one informal settlement. Thus, there is also the motivation to test the impact of public lighting in informal settlements at a larger scale. At some point, there are probably diminishing returns to how useful larger RCT's would be to policymakers, however, such research would be important to the ongoing academic discussion about the role of public light in life at night in this context. It might also help lead to a better understanding of the cost effectiveness of public lighting.

Finally, this thesis only scratches the surface of what can be learned by studying nighttime pedestrian activity in informal settlements. In addition to urban planning and public health, which

[82] More information about Lighting Africa can be found here: https://www.lightingafrica.org/

I discussed, there are also implications for economics in understanding how and when people move at night in terms of business activity and local economic opportunities. Furthermore, there is the ever-present concern about security and crime in informal settlements. UN Habitat has emphasized the importance of security in informal settlements as well as the primacy of streets in driving urban prosperity in two separate reports (Mboup, 2013; UN-Habitat, 2011), indicating that there are important issues that are worth studying at the intersection of these two concepts that can improve the lives of the large and growing number of people living in these neighborhoods worldwide.

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