Slum Upgrading and Long-run Urban Development: Evidence from Indonesia *

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Abstract

Developing countries face massive urbanization under weak property rights. Slum upgrading is a popular policy to improve shelter for many, but preserving slums at the expense of formal developments may entail future opportunity costs. We investigate these dynamic inefficiency concerns by estimating the long-term impacts of the 1969-1984 KIP program, which provided basic upgrades to 5 million residents in Jakarta, Indonesia. We assemble high-resolution data on program boundaries and current outcomes, including novel photographs-based slum indexes. Among historical slums, KIP areas today have on average 15% lower land values, 50% fewer high-rises, and are more informal, consistent with delayed formalization. A boundary discontinuity design yields similar results. Surplus calculations show heterogeneous opportunity costs, with 90% of the losses concentrated in half of the program areas, where land values are high. Elsewhere, KIP delivers sizable surplus. Our exercise informs the debate on whether to upgrade or formalize slums as cities expand.

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1 Introduction

Developing countries are expected to undergo massive urban expansion to accommodate two billion more people by 2050 (Glaeser and Henderson, 2017). As cities are reshaped through a combination of vertical densification and sprawl (Lall et al., 2021), there will be profound implications for urban connectivity, quality of life, and productivity (Harari, 2020). Central to this transformation is the allocation of land, an increasingly scarce resource. This process is complicated by weak property rights and the ensuing politically-charged debate around clearing and redeveloping slums, which host one billion people globally (United Nations, 2020). Yet, there is limited quantitative evidence on this issue due to a lack of data and endogeneity challenges associated with studying slums (Field and Kremer, 2008).

We fill this gap by investigating slum upgrading, an increasingly important policy implemented in many cities.[1] The 1969-1984 Kampung Improvement Program (KIP)[2] provided basic public goods and a verbal non-eviction guarantee to 5 million slum dwellers in the city of Jakarta, Indonesia. Upgrades can be a cost-effective way to improve the well-being of many residents, as documented for KIP (World Bank, 1995). However, there are concerns that preserving slums at the expense of formal developments can give rise to opportunity costs from land misallocation.

This paper makes three contributions. First, we provide novel causal estimates of the long-term impacts of one of the world's largest slum upgrading programs. Studying KIP as modern Jakarta grows out of informality provides a useful setting to understand how the direct benefits of upgrades can be overturned by the long-run costs from delayed formalization, casting light on the classic phenomenon of dynamic inefficiency in cities (Krugman, 1991). Second, we combine administrative data and an innovative photographic survey to capture prices, quantities, and quality in both formal *and informal* real estate markets. Our representative and granular data allows us to develop credible research designs. Third, we quantify the key trade-offs associated with upgrading (and preserving) slums, thus informing policy makers considering slum upgrading and debating whether to formalize slums as cities expand (Duranton and Venables, 2018).

To estimate the long-term causal effects of KIP, we begin by combining policy maps, current assessed land values, as well as building heights and informality from our photos. Our first empirical strategy restricts the sample to historical kampungs that existed before KIP and com-

[1] Slum upgrading programs have been recently announced in India and in Indonesia (World Bank, 2018; Government of India, 2016). Other similar programs include the Favela-Barrio project in Brazil, the PRIMED project in Colombia, and programs in Bangladesh, Tanzania, Kenya, and Ghana (UN Habitat, 2011; World Bank, 2017; UN Habitat, 2017).

[2] *Kampung* is a colloquial term used in Indonesia to describe traditional (rural and urban) villages. Unless stated otherwise, we will use the terms slums, informal settlements, and *kampungs* interchangeably.

pares treated ones with those that were never treated, within the same neighborhood. Our second approach yields similar results using a boundary discontinuity design within 200 meters of KIP boundaries, utilizing the high-resolution policy maps. While KIP planners targeted slums in the worst conditions in the 1960's, our comparisons address program selection bias by comparing KIP areas with nearby counterfactuals that likely belong to the same real estate market by now.

On average, KIP neighborhoods today have 15% lower land values and half as many tall buildings (defined as having more than three floors). We also find evidence of delayed formalization, by constructing novel metrics of informality that utilize both photos and administrative data. Our photos-based indices imply that KIP areas have lower quality by 0.3 standard deviation units, worse vehicular access, and structures that are more irregular and less permanent. KIP areas also have a 3% higher share of unregistered land parcels, based on a unique administrative dataset on titles.

Next, to shed light on where dynamic inefficiency can occur, we exploit the large scale of the program, spanning 110 square kilometers (25% of Jakarta's area). Absent panel data in real estate values, which is rare for informal markets, we trace out the differential evolution of KIP and non-KIP areas in neighborhoods at different stages of urban development. Intuitively, the opportunity costs from delayed formalization will most likely manifest in places where redevelopment is the most profitable. To proxy for real estate market potential, we predict a land index for 2,058 hamlets in Jakarta using non-KIP land values. For hamlets in the bottom quintile of our land index, we estimate a *positive* and significant KIP effect of 10 log points on land values, consistent with the standard result on the capitalization of place-based improvements (Kline and Moretti, 2014). However, moving towards areas with higher predicted land values, we see a reversal in market outcomes as non-KIP neighborhoods formalize. Accordingly, the point estimates begin to attenuate, culminating in a large *negative* effect of -30 log points in the top quintile.

Due to weak property rights, the lower land values in KIP are not sufficient to conclude inefficiency. There are significant barrriers to formalization even whilst land markets function relatively well within the informal and formal sectors (Henderson, Regan and Venables, 2020). Because the law does not require developers to compensate residents without titles, formalization can be privately profitable but socially inefficient if the gains are not large enough to offset the loss in informal surplus associated with evicting kampung residents.

We integrate the findings above to empirically assess the counterfactual surplus in non-KIP neighborhoods relative to KIP. This exercise utilizes our reduced form estimates and data on prices, quantities, and land use maps to capture the key trade-offs involved in redeveloping slums: formalization yields taller and more valuable structures, but displaces slum residents and destroys informal structures, which can involve sizable built-up volume and surplus from horizontal coverage and densification (Henderson, Regan and Venables, 2020). We begin by considering the value of real estate, an important object as it constitutes two thirds of the private capital stock in developing countries (World Bank, 2006). We then incorporate demand and supply elasticities to consider consumer and producer surplus.

Our exercise uncovers significant heterogeneity, with inefficiency occurring in half of the upgraded areas and KIP providing sizable surplus elsewhere, where it hosts around 3 million residents. Notably, 90% of surplus losses are concentrated in the first two quintiles of our predicted land index, comprising 47% of KIP's coverage area. In the top quintile, total KIP surplus is lower by US$2,369 per square meter stemming from 35% lower land values and 29% lower heights. However, the difference more than halves ($1,044 per square meter) in the second quintile, and again in the third quintile. Elsewhere, KIP neighborhoods deliver more surplus. In the lowest quintile, KIP surplus is greater by US$347 per square meter. Overall, this points against inefficiency in areas outside the top quintiles. We then apply our framework to a few case studies in Jakarta to underscore the institutional challenges and equity considerations associated with kampung clearance. We highlight that redevelopments that are efficient from society's perspective did not deliver Pareto gains for kampung residents. Formalization will also potentially involve relocating millions of KIP residents, which can be complex.

Next, we explore some of the factors underlying delayed formalization in KIP. Besides the higher land values from KIP upgrades, which in themselves deter redevelopment, the improvements and non-eviction guarantees can make KIP kampungs more attractive and encourage residents to stay. Over time, this can lead to greater population density and more fragmented land (as stayers sub-divide land parcels). In line with this, KIP areas today have 39% higher population density and 9 more parcels per unit area (47%), which can be associated with higher costs to relocate slum residents and higher land assembly costs. Qualitatively, this holds even in areas in the bottom quintiles of our land index, that have not formalized yet. Additionally, we find suggestive migration patterns consistent with residents remaining in KIP. Pre-KIP population density is a confounder but cannot explain away the results (Oster, 2019).

In addition, we consider the direct effects of the upgrades using detailed maps of KIP investments. Notably, we find that four decades after the program there are no differential effects by the type and intensity of the upgrades, in line with their 15-year projected useful life (Darrundono, 1997). Turning to access to current public amenities, we do not find large differences by KIP status. However, non-KIP neighborhoods tend to have more formal office and retail density (4 and 1 percentage points respectively).

We perform a battery of robustness checks. First, we exploit the staggered roll-out of KIP across three waves to assess program selection bias. We estimate a monotonic pattern with the worst outcomes for the earliest wave, in line with the selection rule which prioritizes kampungs with worse neighborhood quality. Importantly, this pattern disappears in our historical kampung specification, reinforcing our assumption that the selection bias is adequately accounted for. Additionally, to assess confounding by the generic persistence of slums, we repeat our boundary discontinuity analysis using placebo borders from non-KIP historical kampungs, finding no discontinuity. We also address contamination by spatial spillovers and administrative boundaries. While some of the effects may reflect mere reshuffling, we provide suggestive evidence of KIP-induced displacement of development activity away from areas with high land values.

Furthermore, we validate our land values results by showing that they line up well with those for heights. We can account for 90% of the land values effect by imputing the hedonic value of the missing tall buildings in KIP. This assuages the concern that land values may not be accurately measured in (informal) KIP areas, since heights represent real quantities from our representative photos sample and our imputing exercise only uses land values in non-KIP areas.

Beyond Indonesia, our findings deliver lessons for policy makers considering slum upgrading today. In cities at earlier stages of development,[3] slum upgrading may offer an attractive cost-benefit balance for prolonged periods as evidenced by the positive KIP effects we still find in some neighborhoods today. Delaying formalization also allows residents to remain longer in affordable housing. In other cities, the opportunity costs from land misallocation can be large and potentially mitigated by strengthening land market institutions to share surplus with informal residents.

Our paper is related to several lines of research. In recent work on urban development under weak property rights, Henderson, Regan and Venables (2020) and Gechter and Tsivanidis (2018) highlight misallocation and opportunity costs of land use in the context of slums in Kenya and India, respectively.[4] We complement their findings leveraging policy variation from KIP.

Second, we relate to the literature on shelter provision and slum policy in developing countries. Michaels et al. (2021) find positive long-term impacts of a "sites and services" program in Tanzania, which provided public goods on vacant land. They also present descriptive evidence on upgraded slums, finding negligible or negative impacts. Another line of research focuses on public housing.[5] We contribute policy lessons on slum upgrading, which is highly relevant for many cities

[3] When KIP was implemented the average GDP per capita for Indonesia was \$1,033, comparable to Bangladesh (\$1,054), Kenya (\$1,232), Pakistan (\$1,242), and Tanzania (\$915). All dollar amounts are 2015 USD.

[4] As we shed light on the challenges of promoting urban development under weak institutions, we also highlight frictions that echo the urban economics literature on land assembly costs (Brooks and Lutz, 2016), property rights and land fragmentation (Libecap and Lueck, 2013), coordination failures (Hornbeck and Keniston, 2017), path dependence (Bleakley and Lin, 2012), zoning and land use regulations in the United States (Turner, Haughwout and Van Der Klaauw, 2014) and in India (Duranton et al., 2015).

[5] Picarelli (2019) and Barnhardt, Field and Pande (2017) highlight potential losses in job access and the disruption of

with limited vacant land and resources to provide shelter at scale.[6]

Third, we contribute to the literature on place-based policies (Kline and Moretti, 2014), showing how, in a setting with weak property rights, neighborhoods can have lower land values after upgrades.[7] Even though prices in (informal) KIP places are lower than in (formal) non-KIP places, this does not imply that KIP reduced residents' welfare: on the contrary, delayed formalization plausibly allowed KIP residents to stay in the neighborhood longer (Field, 2007), relative to residents of non-KIP kampungs, who were evicted without compensation. This example shows how land values for places can be decoupled from welfare considerations for people when land market institutions are weak.[8]

Fourth, we add to the literature on the measurement of urban form through imagery (Glaeser et al., 2018; Baragwanath et al., 2021).[9] In particular, our informality indexes address the notoriously difficult problem of defining and measuring urban informality. Our photos-based indices overcome coverage bias by complementing Google Street View with photos we took in kampungs inaccessible to Street View cars. We augment this with administrative data on titles and cadastral maps, thus capturing the multidimensional aspects of slums.

The rest of the paper proceeds as follows. Section 2 discusses the background, Section 3 describes the data, Section 4 illustrates the empirical strategy, Section 5 presents our main results, Section 6 explores potential channels, Section 7 discusses surplus considerations, Section 8 addresses identification threats and robustness, and Section 9 concludes.

networks following relocations to public housing in the periphery. Other studies find some positive impacts (Franklin (2019), Franklin (2020), and Kumar (2021)), particularly for programs that did not require relocating to far-away areas.

[6]In addition, Libertun de Duren and Osorio (2020) find limited medium-term impacts associated with the Favela-Barrio slum upgrading program in Brazil. Beyond pubic housing, sites and services, and slum upgrading, the literature has also examined titling (Field, 2007; Galiani and Schargrodsky, 2010), the provision of local public goods (Feler and Henderson, 2011; Castells-Quintana, 2017), housing improvements (Galiani et al., 2017) and the political economy in slums (Marx, Stoker and Suri, 2019). Also see Brueckner and Lall (2015) and Marx, Stoker and Suri (2013) for an overview.

[7]Previous studies have focused on settings with well-defined property rights, largely in developed countries (Neumark and Simpson, 2015). In urban Mexico, McIntosh et al. (2018) and Gonzalez-Navarro and Quintana-Domeque (2016) find that infrastructural improvements increase land prices in the short run for low-income neighborhoods where tenure security is not contentious.

[8]The reason why lower prices in KIP places do not imply lower welfare for KIP residents is that non-KIP prices may not internalize the welfare of kampung residents who are evicted upon formalization. If land markets were perfect, comparing the price developers pay to non-KIP kampung residents against the counterpart for KIP kampungs would capture the welfare effects of KIP on its residents.

[9]Remotely-sensed imagery has been employed to map slums (see Kuffer, Pfeffer and Sliuzas (2016) for a review), but this approach can miss many attributes visible from the ground. Ground imagery from Google Street View has been utilized to detect urban change in the United States (Naik et al., 2017), but this can be problematic in developing country cities due to coverage bias.

2 Background

Indonesia is the fourth most populous country in the world with 240 million inhabitants (World Bank, 2016). Jakarta, the capital, has close to 11 million residents and is part of the sprawling metropolitan area of Jabodetabek (Haryanto, 2018),[10] the world's second-largest, home to 30 million inhabitants and over 5 million commuters (Rukmana, 2015). Below, we describe the history of KIP and discuss how KIP interacts with urban development in modern Jakarta.

2.1 The Kampung Improvement Program

KIP is one of the earliest and largest slum upgrading programs ever implemented. The program in Jakarta covered 110 square kilometers and 5 million beneficiaries, with a total outlay of approximately $500 million (2015 USD). KIP was later expanded to other cities, eventually covering 500 square kilometers and 15 million beneficiaries in Indonesia (see World Bank (1995), Darrundono (1997), and Darrundono (2012) for more details about KIP). This study considers the first three waves of KIP upgrades implemented in Jakarta between 1969 and 1984.

The earliest slum interventions date back to the 1920's, when the Dutch upgraded traditional settlements (*kampoeng verbeteering*) surrounding their communities. After independence, rapid in-migration raised concerns about floods, fires, and riots in kampungs. At that time, Indonesia was one of the poorest countries in the world (with a GDP per capita below that of India, Bangladesh, and Nigeria). Slum upgrading thus appeared as an affordable policy option to benefit a large number of kampung residents (Darrundono, 2012).

Program Details. The primary objective of KIP was to improve neighborhood conditions in kampungs. Given the limited budget and to avoid attracting high-income groups, the upgrades were basic, with a useful life of 15 years (Devas, 1981). Residents were not relocated.

To encourage residents to invest in their properties, KIP planners verbally promised not to evict them for 15 years (Darrundono, 2012, p. 50). Given the challenges in establishing property rights, it is common to bundle upgrades in slums with some form of tenure security (verbal guarantees or occupancy certificates) in order to stimulate private investments (Fox, 2014).

KIP provided three types of physical upgrades. First, the government wanted to improve access to kampungs, particularly in case of emergencies, by widening and paving roads, bridges, and footpaths. The second component focused on sanitation and water management, including public water supply and drainage canals to address flooding. Third, KIP provided community buildings such

[10]Jabodetabek comprises Jakarta and the adjacent municipalities of Bogor, Depok, Tangerang, and Bekasi.

as primary schools and neighborhood health clinics. Figure A1 shows an example of a kampung before and after KIP upgrades.

KIP had a staggered roll-out over three five-year plans (*Pelita*): *Pelita* I (1969-1974) , II (1974-1979) and III (1979-1984), after which it was interrupted due to budget cuts following the 1986 oil shock. The roll-out prioritized kampungs in worse conditions. Specifically, planners created a scoring rule that ranked kampungs based on physical characteristics (e.g. sanitation facilities, flood damage, and road quality), age of the kampung, population density, and estimates of income (KIP, 1969). Given time constraints and limited information, the scoring rule over-weighted physical conditions that were easy to observe. Moreover, kampungs had to be distributed evenly across the five districts of Jakarta.

Descriptive evidence of early impacts of KIP KIP is generally held up by practitioners and policy makers as an example of a successful slum upgrading program (Devas (1981), Taylor (1987), World Bank (1995), Darrundono (1997), and Darrundono (2012)). A 1995 evaluation report by the World Bank concludes that KIP "improved the quality of life of Indonesian urban areas at a low cost of investment" (World Bank, 1995, p. 71).[11] Below, we highlight several points that are relevant for our study.

First, neighborhood conditions and residents' education and well-being improved in KIP.[12] Crowding-in of private investments was also documented, as residents upgraded their dwellings. There was suggestive evidence of higher prices in KIP neighborhoods although the report notes that many non-KIP kampungs had "caught up" (p. 6), as a result of broader economic growth.

In addition, KIP was considered "crucial to establishing the permanence of the kampungs" (p. 59) and associated with strengthened perceptions of tenure security by residents. Even though respondents "had no land certificate or document to prove [ownership]" (p. 111), 47% of KIP respondents claimed ownership rights compared to 32% in non-KIP (Table 13).

Finally, the report recognizes that rising demand for urban land would make the redevelopment of kampungs more common, potentially leaving KIP kampungs behind. The conclusion is that policy makers considering slum upgrading in the future should be "taking into account when and how the ... transformation of improved kampungs into modern real estate is likely to take place." (p. 50). This process was interrupted when real estate markets crashed during the 1997 Asian Financial Crisis, and would only resume in the mid-2000's.[13]

[11]The findings are based on extensive interviews with multiple stakeholders and surveys of two KIP kampungs in central Jakarta as well as one non-KIP kampung in the periphery.

[12]KIP areas experienced improvements in water access, roads, and flood management. "Residents are better educated and healthier, household size have declined, more residents are employed and have greater income" (p. 6) (World Bank, 1995).

[13]For example, according to The Skyscraper Center (2019), virtually all skyscrapers in Jakarta were built after 2005.

2.2 KIP and kampung redevelopment

Today's Jakarta provides an ideal setting to study the dynamic inefficiency concerns alluded to in the World Bank report. The city currently faces an annual population growth rate of 2.5% (World Population Review, 2018) and a severe housing backlog, with an estimated 70,000 additional housing units needed every year (Mardanugraha and Mangunsong, 2014). To address concerns of overpopulation and sprawl, the most recent Master Plan explicitly promotes the redevelopment of central areas (Human Cities Coalition, 2017). However, this process is contentious as rehousing kampung residents is very challenging. Only 14,000 public housing units have been built since the late 1980's.[14] Below we discuss the current status of kampungs, the redevelopment process, and how it is affected by slum upgrading.

Kampungs are estimated to host a quarter of Jakarta's population (McCarthy, 2003). They are relatively high-quality, with fairly permanent structures and access to basic amenities. According to our survey, most residents (75%) are owners, but only 25% report having a formal title.[15] This reflects the segmentation of Indonesian land markets: a formal one with well-defined property rights, originally established by the colonial administration in Dutch settlements, and an informal one that follows local customary law (*adat*).

Redeveloping kampungs into formal neighborhoods is complex (Leitner and Sheppard, 2018). The process to formally register titles entails significant transaction costs, including high fees (8.5%), challenges in verifying tenure status and resolving disputes, and delays when courts are backlogged. Redevelopment also requires thorny negotiations, involving developers, residents, government officials, and middlemen. Local governments fear political backlash from slum clearance, as residents contend that they are not compensated adequately, if at all. In addition, assembling many contiguous land parcels in dense kampungs is a process fraught with holdout problems (Brooks and Lutz, 2016).

Preserving slums is one of the inherent objectives of slum upgrading programs as these neighborhoods provide shelter to many residents. There are several ways in which these programs can delay formalization. First, higher land values from the upgrades will increase redevelopment costs. Moreover, upgrades and non-eviction guarantees can make slums more attractive and strengthen

By the late 1990's, there were still only twenty luxury apartment complexes (Firman, 1999).

[14] Indonesia requires an estimated one million new units per year, of which 40% are provided by developers and 20% by the government, while the rest are self-built informally (The Jakarta Post, 2017).

[15] In 2016 we conducted a field survey with 300 households in eight kampungs, with the local government's permission. 77% of houses had brick or concrete walls, 93% reported having metered electricity, 79% utilized private water supply, and 71% had private toilets. However, the roads are narrow, with only 12% of residents reporting that their street had car access. The average annual household income was US$3,500 and the annual rental cost US$1,600. See Wong (2019) for more details.

residents' perceptions of their occupancy rights (De Soto, 1989). This can encourage them to stay, plausibly leading to greater population density and more fragmented land (as stayers sub-divide land parcels) over time, which increases relocation costs and land assembly costs. Taken together, these factors potentially contributed towards higher perceived formalization costs in KIP areas. Indeed, developers accounted for KIP status as they selected sites for development (World Bank, 1995).

In order to assess whether delaying formalization is efficient, a trade-off needs to be considered between the gains in real estate value associated with redevelopment versus the loss of shelter for many kampung residents. The empirical objects we estimate include the impacts of slum upgrading on land values and built-up volume, which in turn depends on building heights (higher in formal areas) and horizontal coverage (greater in dense slums). We quantify these trade-offs on a neighborhood-by-neighborhood basis. We utilize granular data on land values and building heights to pin down surplus in KIP neighborhoods. We then develop research designs to estimate counterfactual gains for observably identical non-KIP neighborhoods that are more likely to have formalized. We describe the data and empirical strategy next, then turn to surplus.

3 Data

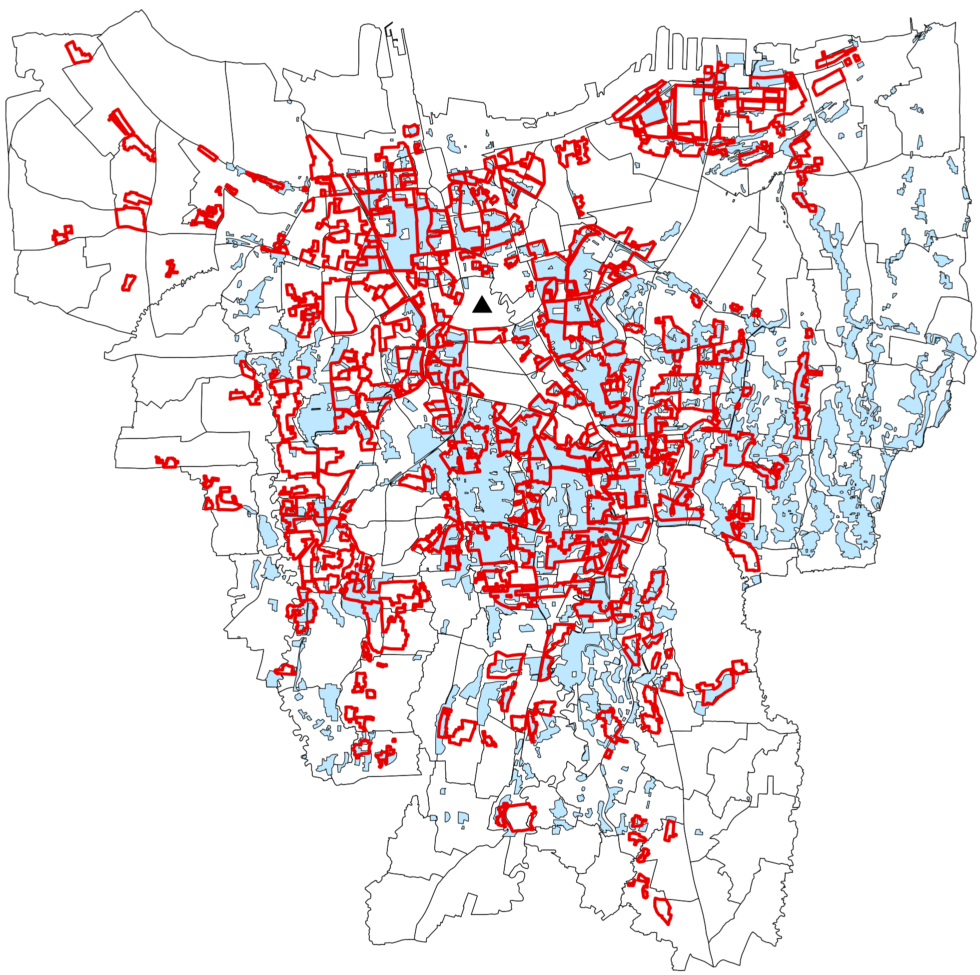
This Section discusses the data we assembled, including policy maps and our primary outcomes, assessed land values and building heights. We then describe our novel measures of informality and additional data. More details about data sources and processing are provided in the Data Appendix. Table A1 presents summary statistics for our outcomes and controls.

3.1 Policy maps

We utilize high resolution (2.5 meters) maps from the Jakarta Department of Housing (DPGP, 2011), indicating the boundaries of KIP upgraded areas and the individual assets provided as part of KIP (including roads, sanitation facilities, and community buildings). An example map is provided in Figure A2. Figure 1 displays KIP treated areas as unshaded polygons.

For the boundary discontinuity exercise, we manually select a subset of 123 "clean" boundary segments such that the control group is not contaminated by treated areas nearby (Turner, Haughwout and Van Der Klaauw, 2014). These boundaries are evenly distributed across Jakarta (Figure A3). Details of the selection procedure are provided in the Data Appendix.

Figure 1: KIP boundaries and historical kampungs



Notes: Map showing KIP boundaries (thick red border) and historical kampungs that existed before KIP (shaded regions). The grey borders are locality boundaries. The black triangle is the National Monument (the 1950's city center).

3.2 Assessed land values

We observe current assessed land values in Jakarta from a digital map obtained in 2015 through the Smart City Jakarta initiative. In an effort to improve property tax collection, the Indonesia land agency developed a mass property appraisal valuation model, similar to those used in developed countries, relying on transactions and market data from brokers, online websites, administrative records, and notary offices. Adjustments are then made based on property and neighborhood attributes (verified by field visits), data quality, and the timing of the transaction. The estimated property value is then decomposed into a building component (imputed using replacement costs) and a land component (*nilai tanah*), which is what we consider.

We have assessed land values in Rupiah per square meter for nearly 20,000 sub-blocks (the smallest zoning unit in Jakarta), evenly distributed throughout the city (Figure A4). The average land value is 12 million Rupiahs per square meter (around US$90 per square foot).

Reliable land value data is challenging to obtain in developing countries. In Jakarta, properties are transacted actively in both the formal and informal markets. Property rights in the latter are informally established using local tax records and sales receipts that are recorded in local administrative offices (Leaf, 1994). We validate our land values data in two ways. First, we cross-check our price effects against real quantities by collecting our own data on building heights. Second, we correlate our land values with 4,000 transactions prices which we scraped and manually geo-referenced from Indonesia's largest property website, obtaining a correlation coefficient of 0.56 (see Figure A5).

3.3 Building heights

We measure building heights from a novel photographic survey we collected. The unit of observation is a 75 meter-by-75 meter pixel.[16] We draw a representative sample of 19,518 pixels from the full Jakarta grid of 89,000 pixels, stratifying by distance terciles to the city center (National Monument).[17] For each pixel, we obtain 4 photos, corresponding to the north, south, east, and west angles from the pixel's center.

The main advantage of our approach is the ability to construct a representative sample including both formal and *informal* areas. 90% of our photos were drawn from Google Street View imagery. However, Street View cars are typically too large for the narrow streets of some kampungs (8% of pixels) and cannot access private gated developments (2% of pixels). For these areas, we obtained photos from enumerators sent to the field, with the government's permission. Our approach also overcomes the problem of under-reporting of buildings in administrative records (e.g. due to tax evasion).

[16] Each pixel has a size comparable to the land area required for an average high-rise development project in Jakarta, based on reports from the Jakarta City Planning Agency.

[17] We include these strata fixed effects in our regressions. The sampling procedure is detailed in the Appendix.

Our primary height outcome is an indicator equal to one if the tallest building in the pixel is above three floors. Pixels with no buildings (4% of the sample), corresponding to large roads, parks, or empty lots, were assigned a height of 0 and a "no building" dummy; results are robust to excluding those pixels.

3.4 Measuring informality

Defining and measuring urban informality is challenging. We consider several metrics to quantify informality through a combination of imagery and administrative data.

Rank-based index. We construct two novel indexes based on photographs, for a subset of 7,101 pixels (approximately 28,000 photographs we hand-coded) in our primary estimation samples. The first index is rank-based and provides a holistic assessment of the neighborhood's quality. The index takes values ranging from 0 (very formal) to 4 (very informal). Examples of photos that we classified can be found in Figure A6. We trained two research assistants from Jakarta who independently performed the assessment. They were instructed to rely on characteristics of the neighborhood (including the density and irregularity of structures, and cleanliness) and of the buildings (such as the durability of materials and the size of windows). We then averaged both rankings; our results are robust to different aggregation approaches and fixed effects to account for subjective differences. The correlation between the two research assistants' rankings is 0.78.

Attributes-based index. Next, we construct an attribute-based index that quantifies features in three important domains: vehicular access to the neighborhood, neighborhood appearance, and the permanence of structures. Guided by the Jakarta government's criteria to define slums,[18] we coded fifteen binary attributes, which are then averaged and standardized within each subsample into a z-score. Due to the complexity and heterogeneity of the imagery, we manually coded the attributes, as opposed to relying on machine learning approaches. The resulting index takes higher values for locations that have a higher degree of informality than average based on those attributes. The two indexes are positively correlated (0.64). The correlation between the rank-based index and each of the individual attributes is also largely positive (Table A2).

Titles. We observe whether land parcels in Jakarta have registered or unregistered titles, drawing upon unique digital land maps created and made public in 2020 by the Indonesian National Land Agency. As a proxy for informality, we compute the area share of each pixel corresponding to unregistered parcels. Further details on the data cleaning process are in the Appendix.

[18] The Jakarta government defines slums using seven criteria associated with housing conditions, access to roads, drainage, access to drinking water, sanitation, solid waste management, and fire prevention.

3.5 Other data

Historical settlements. We identify areas that were kampungs before the implementation of KIP through two maps, that we georeferenced and digitized, one from 1959 (U.S. Army Map Service, 1959) (with 25 meters resolution) and one from 1937 (G. Kolff & Co, 1937) (11 meters). We consider as historical kampungs areas that are marked as "kampung" in either the 1937 or the 1959 map. These areas correspond to the shaded region in Figure 1.[19] We also use these maps to trace major historical road arteries.

Parcel density. As a metric for land fragmentation, we consider the number of parcels in each pixel based on digital cadastral maps created by the Jakarta Department of Housing in 2011 (Figure A7). Land fragmentation increases land assembly costs to the extent that a developer requiring contiguous land will need to negotiate with more owners, potentially exacerbating holdout problems.

Population density. We draw upon the 2010 complete count Population Census to capture population density and demographics for 10 millions individual in Jakarta, including age, gender, educational attainment, and migration status (based on district of birth and district of residence five years before).[20] The finest geographic unit in the population census that we can geo-reference is the hamlet. In all the corresponding regressions, we average all controls at the hamlet level and consider a hamlet treated if the majority of pixels are in KIP. The conclusions are similar if we require all pixels or any pixel to be in KIP.

Amenities. We capture current amenities from two sources. First, we compute the land share of each pixel corresponding to retail and office buildings respectively, based on a 2014 administrative land use map from the Jakarta Government website. Second, we observe public amenities in 2016 from OpenStreetMap, a public crowd-sourced database. We measure distance from the center of each pixel to the closest school, hospital, police station, and bus stop.

Taken together, the data sources above form the basis of our empirical strategy. As can be seen in the maps, our database is uniquely rich, high-resolution, and with a comprehensive coverage of Jakarta.

[19] KIP areas that do not correspond to historical kampungs are kampungs that were settled post 1959.

[20] The Census surveys households based on physical dwellings, irrespective of their legal status. However, it is notoriously difficult to track people in slums. To assess the extent to which this differs by KIP status, we consider the prevalence of households living with unrelated individuals (presumably tenants - a common living arrangement among informal households). Reassuringly, this is very similar in KIP and non-KIP areas, with, if anything, fewer of them in KIP. Results are available upon request. Household sizes are also similar (Table A15).

4 Empirical framework

We consider the following regression model linking current outcomes (Y) to KIP treatment status and an index capturing local unobserved neighborhood quality (ξ):

$$Y_{ij} = \alpha + \beta KIP_{ij} + \xi_j + \varepsilon_{ij} \quad (1)$$

where unit i is a sub-block (for assessed land values) or 75-meter pixel (for heights) in neighborhood j and ε_{ij} is an error term.

The parameter of interest is β, which captures the long-term impacts of KIP on land values and building heights. The main threat to identification is program selection bias because KIP planners formulated a scoring rule to prioritize low-quality kampungs. To the extent that historical differences are persistent, KIP areas may have worse outcomes today due to selection bias ($E[\xi|KIP = 1] - E[\xi|KIP = 0] < 0$).

Our thought experiment involves two nearby locations (T and C) that were both kampungs before KIP. Unconditionally, T had a lower ξ_{pre} than C, and was selected into KIP on the basis of the scoring rule. Over time, massive urbanization introduced large shocks common to both T and C. Our identification assumption is that T and C have similar real estate potential today, conditional on observables and granular fixed effects.

Our first strategy restricts the sample to historical kampungs that existed before KIP and includes locality fixed effects.[21] Our second strategy is a boundary discontinuity design (BDD) comparing observations within 200 meters of KIP boundaries. Given this narrow distance band, it is plausible that observations on both sides of KIP boundaries face common shocks so that, absent KIP, unobserved real estate potential today would vary smoothly at the program boundaries.[22] We include boundary fixed effects and quadratic distance controls to KIP boundaries; the results are robust to other types of distance controls (e.g. logs).

We include eighteen controls capturing distance to historical landmarks, historical infrastructure, and geography. All are predetermined with respect to KIP. Our landmark controls capture historical neighborhood quality and include distance from the National Monument (the 1950's city center), Old Batavia Castle (the colonial city center), and other colonial landmarks. Our infrastructure controls capture pre-KIP public investments and market access, including distance to

[21] Localities (*kelurahan*) are fine geographic units, comparable to U.S. census tracts, with an average area of 2.5 square kilometers. In some of our analyses we also consider hamlets (*rukun warga*), comparable in size to U.S. census block groups, with an average area of 0.24 square kilometers.

[22] KIP neighborhood boundaries are pre-determined because they largely depend on hamlet boundaries defined during World War II by the Japanese for security purposes.

Table 1: Comparing KIP and non-KIP areas

Unit of analysis:	Sub-block level			Pixel level		
Sample:	Full sample (1)	Historical kampung (2)	BDD 200m (3)	Full sample (4)	Historical kampung (5)	BDD 200m (6)
Panel A: Landmark controls						
Log Distance to Monument	-0.37***	-0.02	0.002	-0.31***	0.001	0.004
	[0.00]	[0.12]	[0.80]	[0.00]	[0.85]	[0.31]
Log Distance to Tanjung Priok Harbor	-0.26***	-0.004	-0.004*	-0.19***	-0.004	-0.002
	[0.00]	[0.67]	[0.08]	[0.00]	[0.31]	[0.16]
Log Distance to Old Batavia	-0.31***	-0.02**	-0.005	-0.28***	0.005	0.08
	[0.00]	[0.01]	[0.66]	[0.00]	[0.64]	[0.33]
Log Distance to Concert Hall	-0.36***	-0.02	0.01	-0.31***	0.003	0.01
	[0.00]	[0.13]	[0.29]	[0.00]	[0.64]	[0.27]
Log Distance to Hotel Des Indes	-0.37***	-0.02*	-0.01	-0.34***	-0.001	-0.00006
	[0.00]	[0.09]	[0.33]	[0.00]	[0.88]	[0.99]
Log Distance to Bioscoop Metropool	-0.41***	-0.01	-0.01	-0.32***	0.01	0.002
	[0.00]	[0.55]	[0.20]	[0.00]	[0.42]	[0.58]
Log Distance to Akademi Nasional	-0.06	-0.03	0.01	-0.08**	-0.01	0.01
	[0.18]	[0.55]	[0.73]	[0.04]	[0.70]	[0.55]
Log Distance to Ragunan Zoo	0.15**	0.01	0.0004	0.07**	0.01	-0.001
	[0.03]	[0.45]	[0.93]	[0.04]	[0.30]	[0.53]
Panel B: Infrastructure controls						
Log Distance to Historical Main Road	-0.33***	-0.05	-0.01	-0.31***	0.002	0.03
	[0.00]	[0.18]	[0.76]	[0.00]	[0.95]	[0.14]
Presence of Wells or Pipes within 1000m	0.08***	0.01	-0.003	0.09***	-0.002	0.002
	[0.00]	[0.24]	[0.44]	[0.00]	[0.89]	[0.47]
Log Average Distance to Railway Stations	-0.64***	-0.02	0.01	-0.52***	0.01	-0.01
	[0.00]	[0.20]	[0.53]	[0.00]	[0.41]	[0.56]
Log Average Distance to Tram Stations	-0.52***	-0.02	-0.002	-0.45***	0.004	0.003
	[0.00]	[0.19]	[0.84]	[0.00]	[0.74]	[0.63]
Panel C: Topography controls						
Elevation, m	-4.90***	-0.58	0.14	-3.90***	-0.25	0.09
	[0.00]	[0.49]	[0.79]	[0.00]	[0.37]	[0.79]
Slope, Degrees	-0.09	-0.20	-0.24	-0.001	-0.06	-0.17
	[0.71]	[0.62]	[0.36]	[0.99]	[0.64]	[0.25]
Log Average Distance to 1959 Waterways	-0.15***	0.002	0.0005	-0.12***	-0.002	-0.0002
	[0.00]	[0.77]	[0.84]	[0.00]	[0.53]	[0.89]
Flow Accumulation	0.12	0.92	0.49	-0.11*	0.18	-0.002
	[0.59]	[0.13]	[0.35]	[0.06]	[0.38]	[0.99]
Log Distance to Coast	-0.22***	-0.005	-0.001	-0.17***	-0.01	0.0005
	[0.00]	[0.75]	[0.83]	[0.00]	[0.32]	[0.92]
Log Distance to Surface Water Occurrence	-0.08	-0.01	-0.004	-0.12*	-0.03	0.01
	[0.38]	[0.88]	[0.79]	[0.10]	[0.33]	[0.49]
N	19848	3144	1291	88861	11002	3835
Geography FE	District	Locality	KIP Boundary	District	Locality	KIP Boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports fixed effect regressions with our controls as the dependent variables and the treatment indicator as the key regressor. For each variable, the top row reports the coefficient, and the bottom row reports the p-value in brackets. The unit of analysis is either a sub-block (assessed land values analysis, columns 1 through 3) or a pixel (heights analysis, columns 4 through 6). Columns 1 through 3 report results for the full sample, the historical kampung sample, and the 200 meter boundary discontinuity design (BDD) sample, respectively. Columns 4 through 6 are similar. Standard errors are clustered by locality except for the BDD sample, where we cluster by KIP boundary.

historical main roads, railway and tram stations, as well as the presence of wells or pipes. Finally, our topography controls capture natural advantage. An important component is flood proneness, as Jakarta lies on a coastal lowland and is often paralyzed by flooding. Absent pre-KIP data on flood proneness, we proxy for it with predetermined geographic predictors suggested by the hydrology literature.[23] All variables are described in the Data Appendix.

Table 1 compares KIP and non-KIP areas to show that while there are initial differences, they become negligible in our primary specifications. We report coefficients from regressing each of the controls on the KIP dummy, using five coarse district fixed effects only (column 1), restricting to historical kampungs with locality fixed effects (column 2) and in the 200m BDD specification with boundary fixed effects (column 3). The first three columns correspond to the sub-block level dataset (for the land values analysis), followed by the pixel-level dataset (for other outcomes). The initially large differences (columns 1 and 4) become negligible in both the historical kampungs and BDD specifications.[24]

5 Main results

In this Section we discuss average and heterogeneous KIP effects on our primary outcomes, land values and building heights. We also address program selection bias, a key identification threat.

5.1 Effect of KIP on land values and building heights

Table 2 presents the effect of KIP on land values (columns 1 and 2). The dependent variable is the log price per square meter in a sub-block, from the assessed land values database. Column 1 reports the historical kampung specification and column 2 presents the BDD analysis. The full set of controls are listed in Table 1.

Our baseline estimate in column 1 shows that land values are lower in KIP areas by 14 log points (15%) compared to historical kampungs within the same locality that were not part of KIP. This specification includes 196 locality fixed effects and is identified from 128 localities spread across Jakarta that have variation in KIP status. In column 2, we present our BDD analysis showing a similar effect (-17 log points) comparing observations within 200 meters of KIP boundaries. We

[23] These variables include elevation, slope, distance from the coast and other water bodies, and flow accumulation. We verify that they are good predictors of contemporaneous flooding in Jakarta as measured by OpenStreetMap. For robustness, we also verify that our results are similar controlling for contemporaneous flood proneness.

[24] Distance to Old Batavia castle, the 17th century city center, and to the Hotel des Indes, at the center of the 19th century expatriates community, are statistically but not economically significant in the historical kampung specification in column 2. KIP observations are respectively 249 and 223 meters closer to the two landmarks, relative to a mean of 13 and 11 kilometers. These differences are insignificant in all other specifications.

include 123 boundary fixed effects and are identified using boundary pairs that provide a different source of geographic variation than the historical sample (see Figure A3). In Section 8.2, we reach similar conclusions after addressing threats due to spatial spillovers and confounding by coinciding boundaries.

Table 2: Effect of KIP on land values and building heights

Dependent variable:	**Log land values**		**1(Height>3)**	
Sample:	Historical kampung	BDD 200m	Historical kampung	BDD 200m
	(1)	(2)	(3)	(4)
KIP	-0.14***	-0.17***	-0.12***	-0.08**
	(0.05)	(0.06)	(0.02)	(0.03)
N	3144	1291	5277	1036
R-Squared	0.73	0.81	0.29	0.38
Distance	Y	Y	Y	Y
Topography	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y
Distance to KIP boundary	N	Y	N	Y
Geography FE	Locality	KIP Boundary	Locality	KIP Boundary

* 0.10 ** 0.05 *** 0.01

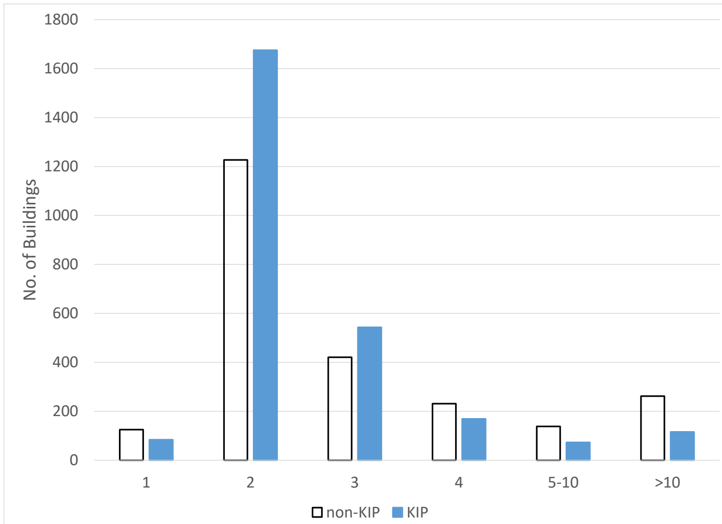
Notes: This table reports the effect of KIP on land values and building heights. Columns 1 and 2 report the effect of KIP on log assessed land values in a sub-block, where the key regressor is an indicator that is 1 for sub-blocks in KIP. Column 1 includes the historical kampung sample with 196 locality fixed effects. Column 2 uses observations within 200 meters from a KIP boundary, controlling for distance to the KIP boundary (and its square), and 123 KIP boundary fixed effects. Columns 3 and 4 present the analysis for heights at the pixel level, where the dependent variable is a dummy equal to 1 if the tallest building in the pixel has more than 3 floors. We also control for strata fixed effects from our photographic survey and an indicator for pixels with no buildings. All other controls are listed in Table 1. Standard errors are clustered by locality (historical specification) and by KIP boundary (BDD specification).

Turning to building heights, we consider as dependent variable a dummy indicating whether the tallest building in a pixel has more than three floors. The unit of analysis is a 75-meter pixel. We add sampling strata fixed effects (from our photographic survey) as well as a dummy for pixels with no buildings (corresponding to public spaces and roads - see Section 3.3).

Our historical kampung sample estimate in column 3 suggests buildings in KIP are 12 percentage points (p.p.) less likely to have more than three floors, relative to observably identical non-KIP areas. This is half of the control group mean (0.24). The estimate for the boundary sample is similar (8 p.p.).

Figure 2 shows that the negative effect is driven by non-KIP areas having more tall buildings. Here, we plot the distributions of building heights by KIP status in historical kampungs. In KIP neighborhoods there is bunching at two floors, the typical height in kampungs. At the right tail, non-KIP areas have twice as many buildings with five to ten floors and also with more than ten floors. We estimate an average effect of -1.6 floors, relative to a mean of 5 for the control group (see Table A3 for estimates using height in number of floors and log height as dependent variables).

Figure 2: Building heights in KIP and non-KIP



Notes: This histogram shows the distribution of building heights for the tallest building in KIP and non-KIP pixels in the historical kampung sample. The horizontal axis represents the number of floors.

Importantly, we demonstrate that the magnitudes we find for building heights corroborate our land values analysis. Translating our height effects into land values, we show that the lack of tall buildings in KIP explains 90% of the aggregate land value impact estimated in Table 2, column 1, mitigating the concern that it may be confounded by differences in the accuracy of land values data in KIP and non-KIP areas. Specifically, we estimate a hedonic regression using land values in non-KIP historical kampungs only and indicators for medium and for tall buildings.[25] We then apply the estimated price premium to impute the land value loss from having fewer tall buildings.[26] This

[25]The key explanatory variables are a dummy for buildings with four to ten floors and a dummy for buildings with more than ten floors. The omitted group represents buildings with three or fewer floors. We include the standard controls for the heights specification, including locality fixed effects. We find a land value increase of 22 log points (25%) for medium-height buildings and 45 log points (57%) for tall buildings.

[26]KIP areas have 145 fewer buildings with more than ten floors. Combined with the 57% price premium in price per square meter (relative to a price of 13.4 millions of Rupiahs per square meter for the omitted group), and assuming a building in each pixel, the total heights effect (expressed in terms of land value) is US$1.3 billion. Similarly, we calculate that the effect for buildings between four and ten floors is US$900 million. Therefore, the aggregate

approach circumvents concerns around measurement error in informal KIP areas (by using land values in non-KIP areas only), and overcomes sample coverage bias (by using heights data from a representative sample). The results are similar using formal areas (defined using our informality index) to estimate the price premium.

5.2 Program selection bias

Next, we address concerns due to program selection bias, ($E[\xi|KIP=1]-E[\xi|KIP=0]<0$). Since the scoring rule formulated by KIP planners prioritized kampungs with low quality first, we use the sequential roll-out of KIP across the three *Pelita* waves (five-year plans) to investigate selection bias. Specifically, we decompose the overall KIP indicator into three dummies corresponding to the three KIP waves and assess whether $\beta_I < \beta_{II} < \beta_{III}$.

Critically, we find a monotonic pattern consistent with selection bias but it disappears in our historical kampung specification. Column 1 of Table 3 shows this pattern using the full administrative data from land assessments, with estimates for the three waves being -0.40 (wave I), -0.29 (wave II), and -0.17 (wave III). We control for district fixed effects, as the selection rule specified that KIP had to be distributed evenly across the five districts of Jakarta, as well as our standard controls. Reassuringly, the differences in column 1 are greatly attenuated in our historical kampung specification. The corresponding estimates are -0.13 (wave I), -0.11 (wave II), and -0.14 (wave III).[27]

Column 3 shows that the conclusions remain the same even after accounting for differences in program design across the three waves. For example, Figure A8 shows that earlier KIP waves were implemented in more central and older parts of the city. We address this by controlling for distance terciles from the center. Moreover, the investments provided by each of the three waves were not identical: for example, the first wave focused on sanitation facilities and the paving of footpaths. We account for this by controlling for the intensity of KIP-provided investments.[28] In addition, we note that there should be little heterogeneity associated with the timing of the investments (which

impact from the heights analysis is US$2.2 billion, which is 90% of the aggregate land value impact for the historical kampung sample (US$2.4 billion).

[27]We implement one-sided hypothesis tests on whether the first wave is better than the second wave and likewise for the second versus the third. A small p-value indicates a high likelihood of the one-sided alternative (a monotonic pattern consistent with the scoring rule). The p-values for the separate one-sided tests are smaller in column 1 (10.8% and 11.9%) than in column 2 (35.7% and 60.9%), in line with the differences being more muted in column 2. In bootstrap simulations with 10,000 iterations, the three coefficients are monotonic in 78% in column 1 but only 24% in column 2.

[28]From our detailed policy maps, we can measure KIP paved roads, sanitation facilities, and public buildings located within 500 meters of each observation (see Section 6.3 below).

Table 3: Heterogeneous effects by KIP waves

Dependent variable:	**Log land values**			**1(Height>3)**		
Sample:	Full sample	Historical kampung	Historical kampung	Photo sample	Historical kampung	Historical kampung
	(1)	(2)	(3)	(4)	(5)	(6)
KIP I (1969-1974)	-0.40***	-0.13	-0.09	-0.13***	-0.10***	-0.08***
	(0.07)	(0.09)	(0.10)	(0.03)	(0.03)	(0.03)
KIP II (1974-1979)	-0.29***	-0.11*	-0.07	-0.10***	-0.10***	-0.08***
	(0.07)	(0.06)	(0.06)	(0.01)	(0.02)	(0.02)
KIP III (1979-1984)	-0.17**	-0.14*	-0.09	-0.04**	-0.07**	-0.05
	(0.08)	(0.08)	(0.08)	(0.02)	(0.03)	(0.03)
N	19848	3144	3144	19518	5277	5277
R-Squared	0.57	0.73	0.74	0.15	0.29	0.29
Distance	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y
KIP investments	N	N	Y	N	N	Y
Distance tercile	N	N	Y	N	N	Y
Geography FE	District	Locality	Locality	District	Locality	Locality

* 0.10 ** 0.05 *** 0.01

Notes: This table assesses whether there is a monotonic pattern in the effects of the three KIP waves that is consistent with the scoring rule prioritizing worse neighborhoods ($\beta_I < \beta_{II} < \beta_{III}$). Specifically, we estimate heterogeneous effects on land values (columns 1 to 3) and building heights (columns 4 to 6) with the key regressors being dummies for each of the three KIP *Pelita* waves (five-year plans). Column 1 includes the full sample of 19,848 sub-blocks from the assessed land values data and 5 district fixed effects. Column 2 restricts to the historical kampung sample with 3,144 sub-blocks and includes 196 locality fixed effects. Column 3 further adds controls for KIP investments (see Table 6) and dummies for distance terciles to the National Monument. Columns 4 through 6 present the analogous analysis for heights. Column 4 includes the full photographic survey sample corresponding to 19,518 pixels. Standard errors are clustered by locality.

have likely depreciated by now, as discussed in Section 6.3) and with some areas having more time to redevelop (since redevelopment would only take off in the mid-2000's, after the 1997 Asian Financial Crisis).

In columns 4 through 6, we replicate a similar analysis for building heights and our results are consistent, with a monotonic pattern in the full sample but no monotonic pattern in the historical kampung specification.[29] Overall, while we observe initial differences indicative of program selection bias, it is reassuring that these differences are greatly attenuated in the historical kampung specifications. These results are in line with descriptions of the convergence of KIP and non-KIP kampungs documented in World Bank (1995).

[29]The corresponding p-values for heights are also smaller in column 4 (13.3% and 1%) than in column 5 (52.5% and 19.9%).

5.3 Heterogeneity by real estate potential

Next, we trace out the effects of KIP across neighborhoods at different stages of development. This exercise informs the dynamic inefficiency concerns associated with slum upgrading (World Bank, 1995). After initial improvements from the upgrades, once formal land values become high enough to justify redevelopment, there may be a reversal in market outcomes as non-upgraded slums formalize and treated slums lag behind. Due to the lack of panel data on land values in developing countries, we will rely on the large geographic coverage of KIP, that spans neighborhoods with different real estate potential. Intuitively, the reversal in land values is more likely in areas where the profits from redevelopment are greater.

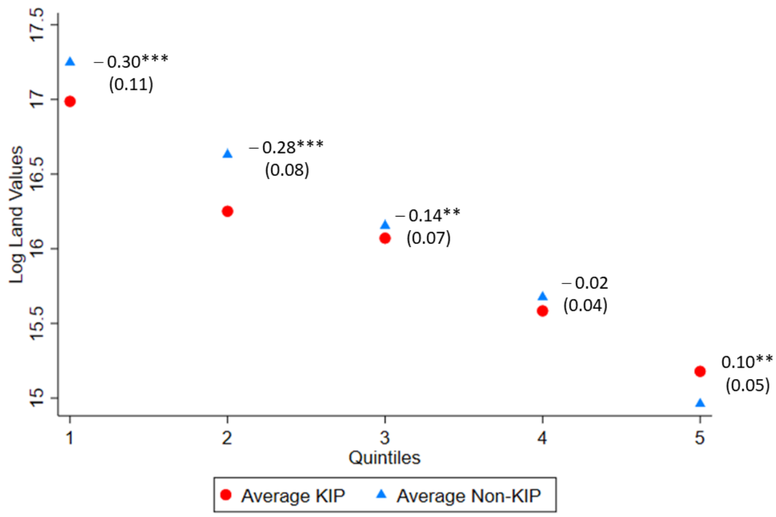
To categorize neighborhoods by real estate potential, we consider our full sample of 2,058 hamlets, which are comparable in area to U.S. Census block groups. Our assumption is that, despite initial differences between KIP and non-KIP, these small geographic units today are subject to common shocks and have uniform potential for redevelopment. We then construct a predicted land index regressing non-KIP log land values on hamlet fixed effects.[30] Figure 3 plots the unconditional means of land values in KIP and non-KIP neighborhoods by quintiles of our index. Additionally, we report the coefficient estimates from a heterogeneous effects regression by quintile that utilizes the full sample of 19,848 sub-blocks with our controls and hamlet fixed effects. These KIP effects are identified from 304 hamlets that have variation in KIP status and are spread across the five quintiles.

We find cross-sectional patterns in line with the dynamics described above. In Q5 (lowest quintile), where formalization is still unlikely as of today, we estimate a positive and significant KIP effect of 10 log points, consistent with the direct benefits of the upgrades being capitalized into land values. The effect becomes negative in areas with greater potential for redevelopment, with the most negative effects in Q1 (-30 log points) and Q2 (-28 log points). These patterns are robust to a variety of approaches to group neighborhoods by real estate potential and to different heterogeneous effects specifications. For example, our assignment to quintiles is very similar if we add controls to the regression that predicts the land index. We also considered distance terciles to the National Monument, although we caution that Jakarta is not monocentric. Furthermore, Table A4 shows that the monotonic pattern in KIP effects from Q1 to Q5 is robust to an alternative specification where we include coarser locality fixed effects.

Potential displacement While it is challenging to quantify the extent to which these spatial

[30] For 674 hamlets without non-KIP land values, we perform an imputation by considering predicted land values at the coarser locality level (480 hamlets) or within a 500 meter buffer (194 hamlets).

Figure 3: Heterogeneity by quintiles of predicted land index



Notes: This figure plots the unconditional means for log land values in KIP (circles) and non-KIP (triangle) neighborhoods, by quintiles of our land index (defined using predicted non-KIP land values). We also report regression estimates and standard errors of the KIP effect on land values across quintiles using the full sample of 19,848 sub-blocks, including our full set of controls and 2,058 hamlet fixed effects. Standard errors are clustered by locality.

patterns reflect a mere reshuffling of development activity, we provide some suggestive evidence of KIP-induced displacement of development activity away from areas with high real estate potential. In Table A4 we provide a formal test and reject that KIP areas in Q1 are more developed (i.e. have higher land values and building heights) than non-KIP areas in Q2.[31] P-values are reported at the bottom of the table (0.01 in all cases). This displacement from Q1 to Q2 is suggestive of an aggregate reduction in realized real estate value.

6 Why do upgraded areas have low land values and heights?

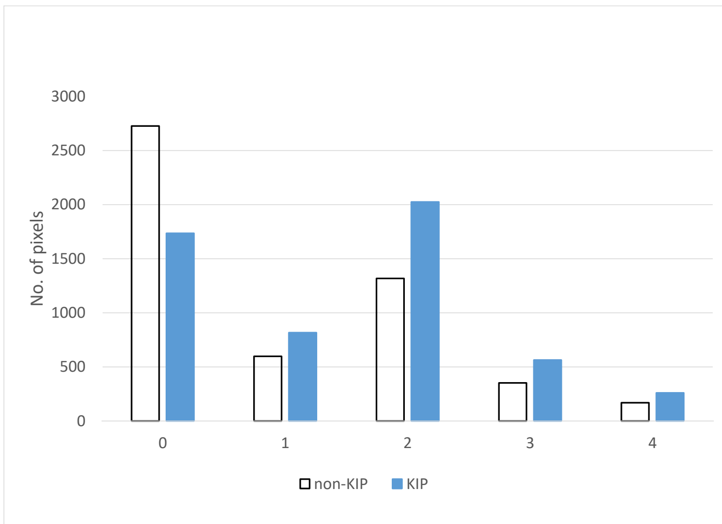
We now turn to examine why KIP areas have lower land values and building heights. In line with the policy makers' perception that upgrading makes slums more persistent, we consistently find that KIP areas are more likely to stay informal across all of our novel metrics of informality. We find less support for other channels including the direct effect of the KIP upgrades and current public amenities.

[31] For this test, we need to compare KIP and non-KIP areas across quintiles with locality fixed effects instead of hamlet fixed effects (which would absorb the non-KIP coefficients).

6.1 Informality

Figure 4 shows that KIP areas are more likely to be informal kampungs today, using the distribution of our rank-based informality index for treated and control pixels, within the historical kampung sample. Here, 0 indicates very formal areas and 4 indicates very informal areas. There is a continuum across the index values, reflecting the varying degrees of informality in a city undergoing urban transformation.

Figure 4: Rank-based informality index in KIP and non-KIP



Notes: This histogram shows the distribution of the rank-based informality index. Index values range from 0, corresponding to "very formal", to 4, corresponding to "very informal". We pool the two samples coded by the two research assistants and report the integer index values.

Table 4 presents the regression estimates indicating that KIP neighborhoods are more likely to be informal across all three of our metrics. On average, the historical kampung specification indicates that the rank-based index is greater by 0.29 (SD of 1), the attribute-based index is greater by 0.05 SD units, and the share of a pixel with unregistered titles is higher by 3 p.p. The patterns are similar in the BDD analysis. Table A5 additionally shows that KIP areas have poorer vehicular access (as proxied by width of roads, quality of pavements, etc.), lower neighborhood quality by appearance (as proxied by the presence of trash, low-hanging wires, lack of drainage canals), and less permanent structures. The signs for these sub-domains of the attribute-based index are consistent with the aggregate effects, although we lack statistical power.

Table 4: Effect of KIP on informality

Dependent variable:	Rank-based index		Attribute-based index		Unregistered parcels (shares)	
Sample:	Historical kampung	BDD 200m	Historical kampung	BDD 200m	Historical kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	0.29***	0.38***	0.05**	0.06	0.03**	0.04*
	(0.05)	(0.13)	(0.02)	(0.05)	(0.01)	(0.02)
N	5277	1036	5277	1036	5277	1036
R-Squared	0.26	0.39	0.17	0.26	0.35	0.40
Distance	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y
Distance to KIP boundary	N	Y	N	Y	N	Y
Geography FE	Locality	KIP boundary	Locality	KIP boundary	Locality	KIP boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports the effect of KIP on informality, using pixel-level specifications similar to those of Table 2, columns 3 and 4. The dependent variables include the rank-based informality index (columns 1 and 2; higher values correspond to more informal), attribute-based index (columns 3 and 4), and area share of a pixel with unregistered titles (columns 5 and 6). Standard errors are clustered by locality (historical specification) and by KIP boundary (BDD specification).

6.2 Density

We now consider land fragmentation and population density. All else being equal, land assembly costs likely increases with more parcels per pixel, as more claimants exacerbate ownership disputes and holdout problems. Similarly, denser neighborhoods increase relocation costs. Both are proximate factors that could contribute towards delaying formalization.

For land fragmentation, column 1 of Table 5 shows that KIP areas have greater parcel density, with an average of 9 more parcels per pixel, relative to a mean of 19 parcels in non-KIP areas in historical kampungs. Besides our standard set of controls, we also include the total log length of roads in the pixel, as the presence of road intersections may mechanically increase observed fragmentation. The BDD estimate is larger (14 parcels, column 2). A back-of-the-envelope exercise shows that KIP's impact of raising the parcel count by 9 translates into a 9% effect on prices (60% of the overall effect of 15%).[32]

In a similar vein, column 3 of Table 5 indicates that population density in KIP hamlets is greater by 33 log points (39%) in the historical kampung sample. Our population density data is at the hamlet level. We control for locality fixed effects as well as our standard controls averaged to the hamlet level. The effect size translates into 51 more people per pixel, in line with the parcel density

[32]We estimate that one additional parcel per pixel in KIP areas is associated with a 1% decline in land values within historical kampungs in KIP. Results are available upon request.

Table 5: Effect of KIP on parcel and population density

Dependent variable:	Parcel density		Log population density
Sample:	Historical kampung	BDD 200m	Historical kampung
	(1)	(2)	(3)
KIP	8.55***	13.84***	0.33***
	(1.07)	(1.29)	(0.07)
N	11002	3835	1184
R-Squared	0.51	0.44	0.56
Distance	Y	Y	Y
Topography	Y	Y	Y
Landmarks	Y	Y	Y
Distance to KIP boundary	N	Y	N
Geography FE	Locality	KIP boundary	Locality

* 0.10 ** 0.05 *** 0.01

Notes: This table reports the effects of KIP on the number of parcels in a pixel (columns 1 and 2) and log population density in a hamlet (column 3). Columns 1 and 2 repeat the building heights specifications of Table 2, adding the log length of roads in a pixel as a control. In column 3, we report effects for population density at the hamlet level with locality fixed effects. The KIP dummy is equal to 1 if the majority of the area in the hamlet is in KIP. Controls are all averaged to the hamlet level. Standard errors are clustered by locality except for the boundary analysis where we cluster by KIP boundary.

estimates.[33] Our data is not granular enough to decompose the effects by migration, fertility, or mortality in a definitive way, but we address these patterns as well as sorting in our robustness checks (see Section 8.3). In particular, we find patterns consistent with KIP residents being more likely to stay in the neighborhood. This is also in line with greater land fragmentation associated with stayers subdividing land over time.

We discuss additional heterogeneous effects in the Appendix. Table A6 shows that KIP areas are more fragmented and denser not simply because control areas are formal, but even in parts of the city where neighborhoods have likely not formalized. In addition, we find that fragmentation is less pronounced where KIP-provided roads formed regular grids.

Pre-KIP population density Table A7 demonstrates that the greater density in KIP today cannot be explained away by KIP areas being denser before KIP. We conduct our parcel density analysis separately for localities with pre-KIP population density above and below median, based on 1961 census records. Columns 1 and 2 show that the KIP effect on parcel density is indeed higher (14.87 parcels) in areas with high pre-KIP density versus areas with low pre-KIP density (9 parcels), in

[33] We estimate that 9 more parcels per pixel implies 36 to 72 more individuals per pixel, assuming one to two households per parcel and an average household size of four.

line with the KIP scoring rule that prioritized places with greater population density.

Crucially, the estimates stabilize across the high- and low-density samples once we add our controls and locality fixed effects. Specifically, 14.87 is statistically significantly larger than 9.00 (p-value: 1.7%) but the difference (8.97 versus 7.78) becomes insignificant with controls (p-value: 31.9%). Following Oster (2019), we assess the relative importance of selection on observables versus unobservables, finding a ratio of 3, comfortably above the heuristic threshold of 1. Moreover, we find stable effects for land values and heights across high and low pre-KIP density samples (available upon request). These tests mitigate concerns that our estimated effects are confounded by pre-KIP density.

6.3 Amenities

Below, we explore the role of amenities by considering initial KIP investments as well as access to current public amenities.

Initial KIP investments. Table 6 shows that the effects on land values are not heterogeneous by the original KIP investments. Specifically, we examine four primary KIP policy components - vehicular roads, pedestrian roads, sanitation facilities, and public buildings (health centers and schools). We observe the location and type of KIP investments from the policy maps.

For each assessed land value observation, we quantify the intensity of KIP investments located within a 500 meter buffer as total length of vehicular and pedestrian KIP-provided roads and number of sanitation facilities and public buildings. We do so for observations in KIP and non-KIP areas, allowing for the possibility that residents in non-KIP areas were also able to access KIP investments. The four investment intensity measures are demeaned so that the coefficient on the treatment indicator corresponds to the average treatment effect (i.e. evaluated at the average prevalence of KIP investments).

Column 1 reports the results for the historical sample and column 2 presents results for the full sample. Interestingly, we do not find differential treatment effects by type of investment on current land values. This suggests that differences in initial public investments may have equalized across KIP and non-KIP areas by now. Given that planners assumed a useful life of 15 years, it is plausible that the initial KIP investments have significantly depreciated after four decades.

Current amenities. Table A8 demonstrates that KIP areas today have similar access to public amenities, but fewer formal amenities. For public amenities (columns 1 to 4), differences in access to the nearest school, hospital, police station, and bus stop cannot explain our results. This corroborates the discussion in World Bank (1995) that KIP accelerated the provision of amenities in treated neighborhoods, but that non-KIP kampungs converged as a result of broader economic

Table 6: Heterogeneous effects by KIP components

Dependent variable:	Log land values	
Sample:	Historical kampung	Full sample
	(1)	(2)
KIP	-0.09*	-0.11***
	(0.05)	(0.04)
Length of Vehicular Roads (in km)	-0.03	-0.02
	(0.03)	(0.02)
Length of Pedestrian Roads (in km)	-0.01	0.01
	(0.02)	(0.02)
Number of Sanitation Facilities	0.005	0.003
	(0.008)	(0.008)
Number of Public Buildings	0.014	-0.000
	(0.03)	(0.02)
KIP X Length of Vehicular Roads	-0.001	0.004
	(0.03)	(0.02)
KIP X Length of Pedestrian Roads	-0.005	-0.005
	(0.02)	(0.02)
KIP X Number of Sanitation Facilities	0.002	-0.004
	(0.007)	(0.008)
KIP X Number of Public Buildings	-0.02	0.03
	(0.03)	(0.02)
N	3144	19848
R-Squared	0.73	0.85
Distance	Y	Y
Topography	Y	Y
Landmarks	Y	Y
Geography FE	Locality	Hamlet

* 0.10 ** 0.05 *** 0.01

Notes: This table reports heterogeneous effects on land values by four policy components (vehicular roads, pedestrian roads, sanitation, public buildings). Column 1 presents the historical kampung specification with locality fixed effects. Column 2 presents the full sample with hamlet fixed effects. The intensity of KIP investments is measured by length of vehicular and paved roads, number of sanitation facilities, and number of public buildings within a 500 meter buffer around each observation. The KIP intensity variables have been demeaned so that the coefficient on the KIP indicator reflects the effects when evaluated at average intensity levels. The omitted category is non-KIP areas. Standard errors are clustered by locality.

growth in Jakarta. In contrast, for formal amenities, columns 5 and 6 show that KIP areas have 1 p.p. lower retail density and 4 p.p. lower office density, in line with our findings of lower land values, lower heights, and more informality.

7 Surplus calculations

Overall, the average KIP neighborhood has lower land values, fewer tall buildings, and is more informal relative to non-KIP. There are also heterogeneous effects across quintiles of our land index. We now integrate these findings in a simple framework to shed light on efficiency concerns related to slum upgrading.

Our exercise compares the surplus in KIP neighborhoods, that tend to stay informal, to the counterfactual surplus in non-KIP neighborhoods, that are more likely to have formalized. We do this neighborhood by neighborhood, spanning local real estate markets at early versus late stages of development. An implication of weak property rights is that developers may not internalize the cost to compensate existing residents when redeveloping kampungs.[34] To account for total surplus from the social planner's perspective, we consider both formal and informal surplus separately. We capture three key aspects: non-KIP areas, which are more likely to be formal, have (i) higher values and (ii) taller structures, but (iii) lower horizontal coverage than slums (Henderson, Regan and Venables, 2020).

To fix ideas, consider the housing space (p,q) in a neighborhood, where q denotes quantities of built-up space and p unit prices (see Figure A10.) Under KIP, the neighborhood is characterized by housing demand D_K and supply S_K and the ensuing equilibrium is (p_K, q_K). In the non-KIP counterfactual, the equilibrium (p_{NK}, q_{NK}) is characterized by D_{NK} and S_{NK}. Our object of interest is the sum of producer and consumer surplus in the KIP and non-KIP equilibrium. For each neighborhood, we pin down KIP surplus using observed prices and quantities in KIP from our granular dataset. We then utilize our estimated KIP treatment effects to back out the implied counterfactual non-KIP prices and quantities.

As a preliminary step, we consider the value of the built-up stock. We add the value of land (from our land assessment data) and structures (from applying construction cost estimates from industry reports to built-up volume). To quantify volume, we combine our data on vertical building heights with administrative cadastral maps on horizontal built-up coverage (35% for KIP and 18% for non-KIP areas).[35]

Next, we move beyond real estate value and consider surplus, which requires additional assumptions. For consumer surplus, we utilize a linear approximation (which we validate),[36] to

[34] Our surplus comparison speaks to the opportunity costs associated with land misallocation. It is worth noting that the lower land values in KIP do not indicate lower welfare for KIP residents because the welfare for evicted kampung residents is not necessarily captured by the higher formal prices in non-KIP neighborhoods.

[35] This is in line with Henderson, Regan and Venables (2020)'s findings for Nairobi, where informal coverage is between 40% and 60% in central areas and formal coverage is 20-30% throughout the city.

[36] We show that the slopes at different points on the demand curve are similar (see details in the Appendix).

quantify the area below the demand curve as that of a triangle. Under this approximation, consumer surplus equals real estate value rescaled by the elasticity of real estate demand.[37] For non-KIP demand elasticity, we adopt 0.2 from Malpezzi and Mayo (1987). We back out KIP demand elasticity (0.16) based on differences in the housing budget shares for rich versus poor households (Badan Pusat Statistik, 2008).

Turning to producer surplus, we integrate the area above the supply curve assuming a Cobb-Douglas production function (Combes, Duranton and Gobillon, 2021). We set (formal) non-KIP and (informal) KIP supply elasticity to 1.4 and 1.3 respectively (Henderson, Regan and Venables, 2020). We discuss robustness in the Appendix. In particular, the patterns remain qualitatively similar when we consider alternative assumptions for elasticities, construction costs, horizontal coverage, and shape of the supply curve.

The results of our exercise are in Table 7. We perform our calculations for all KIP hamlets in Jakarta and report our results averaged by quintiles (rows 1 through 5) and across all of KIP (row 6). Columns 1 and 2 report the treatment effects on land values and heights within each quintile, which we use to retrieve the counterfactual p_{NK} and q_{NK}. Columns 3 and 4 report real estate value, respectively $p_K q_K$ and $p_{NK} q_{NK}$. Columns 5 and 6 report the difference between KIP and non-KIP in real estate value and surplus, respectively. All figures are expressed as 2015 USD per square meter.

We find considerable heterogeneity across quintiles (rows 1 through 5). In the top quintile (Q1), our treatment effect estimates imply land values and heights in KIP are lower by 30 and 25 log points respectively (-35% and -29%). Accordingly, KIP property value is very low ($1,873 per square meter) relative to non-KIP ($3,098), resulting in a difference of $1,225 in value terms and $2,369 in surplus terms. The surplus difference more than halves in absolute terms in the second quintile and again in the third quintile, becoming positive in the last two quintiles. In Q5, where KIP has higher land values than non-KIP, the surplus difference is $347 despite moderately taller formal buildings. Intuitively, as we convert value to surplus, KIP real estate value is weighted relatively more since informal demand and supply are more inelastic. Thus, in Q4 and Q5, the differences in total value of the capital stock are accentuated in surplus terms and become more positive, reflecting a relatively large informal surplus.

Overall, it is striking that the surplus losses are highly concentrated with 90% attributed to the first two quintiles, comprising 47% of KIP's coverage area. Aggregating these surplus differences across the share of KIP areas that are informal (60%)[38] amounts to 25 times the annual rental cost

[37] For example, consumer surplus in KIP is $\frac{p_K^* q_K^*}{2\varepsilon_K}$, where ε_K is the demand elasticity in KIP.

[38] We consider "informal" areas where our rank-based informality index is strictly above 1.

Table 7: Assessing surplus in KIP and non-KIP

		(1)	(2)	(3)	(4)	(5)	(6)
		KIP treatment effects		*Value of built-up stock*		*ΔValue $_{K-NK}$*	*ΔSurplus $_{K-NK}$*
		Log land values	*Log heights*	*KIP*	*Non-KIP*		
(1)	Q1 (highest)	-0.30*** (0.11)	-0.25 (0.16)	$1,873	$3,098	-$1,225	-$2,369
(2)	Q2	-0.28*** (0.08)	-0.01 (0.05)	$1,112	$1,716	-$603	-$1,044
(3)	Q3	-0.14** (0.07)	-0.15** (0.07)	$972	$1,317	-$345	-$382
(4)	Q4	-0.02 (0.04)	0.06 (0.04)	$717	$738	-$22	$398
(5)	Q5 (lowest)	0.10** (0.05)	-0.03 (0.08)	$489	$478	$11	$347
(6)	Overall			$1,113	$1,626	-$513	-$781

Notes: Columns 1 and 2 report regression coefficients and standard errors (in parentheses) for the effect of KIP on log land values and log number of floors across quintiles of our land values index, using the full sample and our full set of controls and hamlet fixed effects. Standard errors are clustered by locality. * 0.10 ** 0.05 *** 0.01. All figures in columns 3 through 6 are in 2015 USD per square meter of land.

in these kampungs from our survey ($2,700). A similar calculation for Nairobi yields 26 times the annual rental cost in slums (Henderson, Regan and Venables, 2020). The surplus difference is marginal or positive, pointing against inefficiency, in the other three quintiles, where KIP comprises 57 square kilometers and hosts an estimated 3 million residents. Here, the wedges between formal and informal land values and built-up volume are relatively modest. Buildings in non-KIP average 2.5 floors only with half the horizontal coverage of KIP. Averaging across all five quintiles (row 6), the average value of KIP real estate stock is lower than in the non-KIP counterfactual by $513, corresponding to a surplus difference of $781. These magnitudes are sizable relative to the average non-KIP real estate value per square meter ($1,396).

Beyond informing where slum upgrading can give rise to inefficiency, the reduced-form comparisons above also shed light on the crucial policy question of how to manage slum proliferation. Notably, the surplus differences between KIP and non-KIP areas represent conservative bounds for the surplus differences from formalizing slums.[39] To illustrate this, we apply our framework

[39] To calculate the surplus gains from formalization, the relevant comparison would be between formal versus informal areas, rather than between KIP and non-KIP. The formal-informal comparison would likely accentuate the patterns we find, with large surplus gains from formalization in Q1 and Q2 that decline moving towards Q4 and Q5.

to case studies of KIP kampungs that were slatted for clearance in 2015-2016 by the Jakarta government. We describe them in detail in the Appendix. These cases show that kampung clearance occurs across all quintiles of our index, including where the societal gains are negative. As notable examples we highlight Kampung Bukit Duri (in Q5), Kali Pessangrahan (Q3), and Kalijodo (Q2), with surplus differences of, respectively, \$572, -\$307, and -\$910. Positive numbers suggest informal surplus is greater and that formalization would represent a net loss to society.

These examples also underscore significant challenges in sharing the societal gains from formalization with kampung residents. Most of them, including those with titles, have yet to receive compensation, as land sale negotiations have stalled, courts are backlogged, and corruption scandals have emerged. A key challenge is relocating kampung residents, even where formalization is associated with large societal gains. For example, residents of Kalijodo (Q2) were offered public housing in Marunda (Wijaya, 2016), 24 km away in the periphery (Q5). We calculate that consumer surplus in Marunda is only 46% of that in Kalijodo, echoing Barnhardt, Field and Pande (2017).

There are a few caveats to our approach. We focus on surplus changes for individual neighborhoods abstracting from city-level effects (agglomeration, congestion, aggregate impacts through property tax revenues, and open-city migration). Moreover, some of the effects on development activity may represent spatial reallocation or displacement due to KIP, for which we find suggestive evidence in Section 5.3. In addition, our land values may not capture some spillovers, including inter-generational externalities (Chetty and Hendren, 2018).

Taken together, our exercise provides a framework to evaluate efficiency considerations associated with slum upgrading. This can inform policy makers considering slum upgrading vis-à-vis other shelter policies, such as public housing. Our results suggest that the gains and losses from formalizing slums are heterogeneous across locations. While the canonical portrayal of progress in cities involves a physical transformation of structures into modern real estate, we highlight that some redevelopments that deliver higher market values are not socially efficient.

8 Threats to identification and robustness

This Section discusses threats to identification, to lend further support to our main findings on land values and building heights. We discuss potential confounding due to the persistence of slums, spatial spillovers, overlapping boundaries, and endogenous sorting. We also describe additional robustness checks.

8.1 Persistence of slums

Table 8 presents a falsification test to address confounding of our BDD estimates due to the generic persistence of slums. We consider 45 historical slum boundaries in non-KIP areas as placebo borders. If historical slums have persistently lower land values, we should find a negative and significant effect when we compare areas that were historical kampungs against areas that were not. Instead, we find an insignificant effect, both with a 200 meter and a 500 meter distance band, consistent with the notion that these areas face common demand shocks by now. In addition, in a pooled specification including both KIP and placebo kampung boundaries we find that the KIP boundary effects are statistically significantly different relative to the boundary effects for placebo kampungs.

Table 8: Effect of placebo boundaries

Dependent variable:	**Log land values**	
Sample:	Placebo Boundaries	
	BDD 200m	BDD 500m
	(1)	(2)
Kampung	-0.003	0.001
	(0.04)	(0.05)
N	1793	2631
R-Squared	0.50	0.50
Distance	Y	Y
Topography	Y	Y
Landmarks	Y	Y
Distance to boundary	Y	Y
Geography FE	Boundary	Boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports the effect of placebo boundaries on land values, where the key regressor is the historical kampung indicator. The sample includes sub-blocks that are not in KIP and are within 200 (500) meters of a historical kampung boundary for column 1 (2), conditional on 45 (41) historical kampung boundary fixed effects. Both control for quadratics in distance to the nearest historical kampung boundary. Standard errors are clustered by boundary.

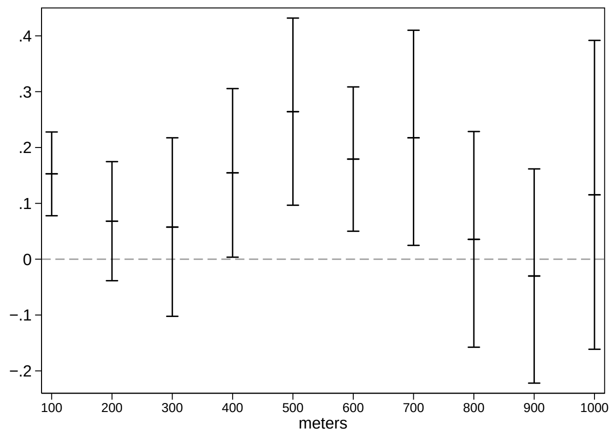
8.2 Robustness for the BDD analysis

Spatial externalities Next, we consider whether spatial spillovers attenuate our BDD estimates. For example, negative spillovers stemming from unsanitary living conditions and depressed public and private investment in slums could lower land values in control areas just outside the KIP boundary. To the extent that localized externalities decline with distance from KIP areas (Turner, Haughwout and Van Der Klaauw, 2014), this should give rise to a spatial decay pattern away from

KIP boundaries.

Figure 5 shows a lack of spatial decay, assuaging the concern that the BDD estimates are attenuated by spillovers from KIP contaminating non-KIP neighborhoods. This is consistent with the prominence of gated communities in formal neighborhoods in Jakarta, which minimizes spillovers from nearby neighborhoods.

Figure 5: Spatial decay: Effect of KIP on land values



Notes: These coefficients reflect differences in land values moving away from KIP boundaries. Each point corresponds to a coefficient and 95% confidence interval for distance bins regressors in the historical kampung sample specification. We extend the specification in Table 2, column 1, by including 10 dummies for distance bins as we move away from the KIP boundary (0 to 100 meters, ..., up to 900 to 1000 meters). KIP is the omitted group. We drop observations beyond 1000 meters since we are identified off of within-locality variation only. The average locality has an area of 2.5 square kilometer, implying an equivalent area radius of 892 meters.

Confounding by coinciding boundaries To probe potential confounding of the BDD estimates by administrative boundaries, in Table A9 we additionally control for locality fixed effects (with a 500 meter distance band), showing that the effects of KIP at the boundary are similar when considering variation within the same administrative unit.[40] Table A10 shows that our results are also robust to excluding KIP boundaries that overlap with historical and contemporaneous waterways (6% of boundaries) and roadways (35%).

Bandwidth Table A11 shows that the boundary discontinuity estimates are similar across different buffer distances ranging from 150 meters (the optimal bandwidth for land values as per Calonico, Cattaneo and Titiunik (2014)) to 500 meters. This corroborates the weak evidence of spatial spillovers above.

[40]Localities are important administrative units in Jakarta. For example, land transfers are recorded in registries in the local *kelurahan* office.

8.3 Endogenous sorting

We consider endogenous population sorting into KIP as a potential confounder. Using data on 10 million individuals in the 2010 population census, our tests suggest that compositional differences that could arise due to endogenous sorting are unlikely to explain our findings. If anything, educational attainment is slightly higher in KIP, for all individuals (Table A12) and when restricting the sample to stayers (Table A13), which tends to go against the lower land values in KIP.

Table A14 further shows in-migration patterns that are inconsistent with crowding by sorting of low-education individuals into KIP: KIP has slightly lower in-migration rates (1 to 2 p.p.) relative to the mean, with migrants having slightly more years of schooling. Table A15 additionally shows that fertility and mortality are comparable and cannot explain the higher population density in KIP.

These patterns corroborate the conclusions in World Bank (1995) that "KIP did not disturb the existing residential stability of the kampungs" and that "residents are ... better educated and healthier" (p. 6).

8.4 Robustness to using the full sample

Table A16 shows that the estimates for all our primary outcomes are similar utilizing the full sample of observations. Overall, this is reassuring as the full sample, the historical sample, and the boundary samples are identified from different sources of variation. In addition, this assuages concerns that our BDD estimates capture only hyper-localized effects. Purely localized effects would be netted out once we average across all locations, leaving small effects in aggregate - which is not what we find. In the full sample, we find a statistically significant land value effect of -11 log points (12%), similar in magnitude to the baseline analysis (15%). The estimates for the other outcomes (heights, informality, parcel, and population density) continue to be economically and statistically significant in the full sample.

8.5 Effects of crowding

We investigate whether congestion associated with higher population density in KIP may reduce land values directly, regardless of delayed formalization. We assess the direct impacts of congestion on land values in non-KIP areas by considering 45 informal non-KIP hamlets with high population density and estimating the spatial decay in land values away from these hamlets. Notably, Figure A9 shows no spatial decay that is large enough to explain our effects. We can statistically reject (at the 5% level) that the direct effect of population density on land values can explain our effect sizes (-0.14 to -0.17).

8.6 Other robustness checks

Below we provide robustness checks that address concerns related to selection in our outcome data, confounding by historical land institutions, and standard errors.

Selection for development activity. We consider selection into development activity stemming from the fact that the potential for building high-rises depends on zoning regulations and market access. Table A17 shows that the results for building heights survive after dropping pixels with no buildings (columns 1 and 2), restricting to pixels zoned for commercial developments (columns 3 and 4), or restricting to pixels within 1000 meters of pre-determined historical main roads, as a proxy of market access (columns 5 and 6).

Selection for land values assessment. Next, we assess whether there are systematic differences in the quality and coverage of the assessed land values data. First, to the extent that the measurement error is smooth across KIP boundaries, it is unlikely that the boundary discontinuity estimates are biased by differences in the land values assessment. Nevertheless, one concern is that KIP areas are more likely to be informal today, and property data for informal settlements are less likely to be reported. On the contrary, Table A18 shows that KIP areas are more likely to appear in the assessed values database. This is consistent with kampung residents recording property transactions in the local administrator's office (Section 3.2).

Historical land institutions. Early Dutch settlements (as identified by our historical maps) may be unobservedly higher-quality or more likely to be titled. In Table A19, we replicate our main specifications (Table 2) dropping hamlets with any Dutch settlements. Reassuringly, our results are very similar.

Standard errors robustness. In Table A20, we replicate the specifications in Table 2 and show that the p-values for the KIP treatment effect are similar under alternative standard errors specifications. For our historical kampung specification, where we cluster by locality at baseline, we consider a coarser clustering by sub-district, as well as Conley (1999) standard errors with a radius of 700 meters, 900 meters (comparable to clustering by locality), and 1200 meters. Moreover, our boundary discontinuity inference - where we cluster by KIP boundary at baseline - is also robust to clustering standard errors at the sub-district level, with p-values of respectively 0.02 and 0.08.

9 Conclusion

Policy makers are debating different policy approaches to accommodate massive urbanization flows. A popular one is slum upgrading, which preserves slums but may entail dynamic inefficiency. In this paper, we contribute to this debate by providing novel causal evidence of the long-term impacts of the world's largest scale slum upgrading program, the Kampung Improvement Program. Our setting is unique in that we have granular data for formal and informal areas for a mega-city that has started formalizing, over 40 years later.

Across empirical exercises and robustness checks, we find a consistent pattern with KIP neighborhoods having 15% lower land values, half as many tall buildings, and being more informal. The scale of the program and comprehensive coverage of our data also allows us to uncover heterogeneous patterns across neighborhoods at different stages of development. KIP areas have higher land values in the bottom quintile of our predicted land index, consistent with positive effects of the upgrades. This effect attenuates and reverses as we move towards the top quintiles, where non-KIP has started to formalize with higher land values. Surplus comparisons between KIP and non-KIP counterfactuals point against dynamic inefficiency outside the first two quintiles.

Our findings shed light on the trade-offs associated with slum upgrading and more broadly on shelter policy considerations for developing country cities, many of which are experiencing a severe housing backlog. Common policies include public housing and sites and services, both of which entail significant costs and require vacant land. By delaying formalization, slum upgrading implicitly provides affordable housing to many residents, potentially millions in the case of Jakarta. Its potential to provide shelter at scale can make it attractive from a cost-benefit perspective relative to other housing policies. At the same time, the upgrades can introduce place-based distortions in the form of land misallocation. Our exercise quantifies these costs to society to inform the choice of the most appropriate policy tool. Some of these costs could be mitigated by complementing place-based upgrades with person-based interventions (Gaubert, Kline and Yagan, 2021).

There are several avenues for future research. First, it will be important to understand the implications of slum residents' location choices on upward mobility. It will also be interesting to study slum upgrading programs in cities at earlier stages of urban development. Finally, our study also points to the use of ground imagery as a promising approach to measure the properties of the built environment. Policy makers are interested in identifying slums for poverty targeting and for tracking their proliferation. Our approach could be scaled up to produce systematic mappings.

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Online Appendix

Appendix Tables

Table A1: Summary statistics

Variable name	N	Unit	Mean	SD
Panel A: Outcomes				
Assessed Land Values, Thousand Rupiahs per sqm	19848	sub-block	12388	14690
1(Height>3)	19518	pixel	0.17	0.37
Rank-Based Informality Index	7101	pixel	1.11	1.12
Attribute-Based Informality Index	7101	pixel	0.00	0.42
Unregistered Parcels (shares)	88861	pixel	0.13	0.20
Parcel Density	88861	pixel	15.86	16.19
Retail Density	88861	pixel	0.02	0.10
Office Density	88861	pixel	0.04	0.16
Population density	2533	hamlet	25698	25918
Panel B: Controls				
Distance to Monument, m	88861	pixel	10707.52	4666.42
Distance to Historical Main Road, m	88861	pixel	6983.48	4448.38
Presence of Wells or Pipes within 1000m	88861	pixel	0.11	0.31
Average Distance to Railway Stations, m	88861	pixel	7391.57	4063.21
Average Distance to Tram Stations, m	88861	pixel	8334.91	4173.37
Distance to Tanjung Priok Harbor, m	88861	pixel	15920.54	6200.10
Distance to Old Batavia, m	88861	pixel	12560.57	5879.22
Distance to Schouwburg Weltevreden Concert Hall, m	88861	pixel	11113.72	4774.49
Distance to Hotel Des Indes, m	88861	pixel	11283.16	5105.56
Distance to Bioscoop Metropool, m	88861	pixel	10096.05	4108.94
Distance to Akademi Nasional, m	88861	pixel	11528.63	5708.23
Distance to Ragunan Zoo, m	88861	pixel	13580.41	6654.04
Elevation, m	88861	pixel	21.91	14.78
Slope, Degrees	88861	pixel	4.86	3.38
Average Distance to 1959 Waterways, m	88861	pixel	2754.79	1212.98
Flow Accumulation	88861	pixel	2.91	7.24
Distance to Coast, m	88861	pixel	11501.98	6926.17
Distance to Surface Water Occurrence, m	88861	pixel	2427.23	1509.44

Notes: Panel A reports summary statistics for outcome variables, including land values (for 19,848 sub-blocks in the administrative database for land values) and building heights (for 19,518 pixels in our photographic survey). Additionally, we manually reviewed the appearance of the photos for 7,101 pixels to construct the rank-based and attribute-based informality indexes. We also report land use patterns (parcel, retail, and office density) for 88,816 pixels from an administrative dataset, and population density for 2,533 hamlets from the 2010 Population Census. Panel B reports summary statistics for controls measured at the pixel level.

Table A2: Rank-based informality index and attributes

Dependent variable:	**Rank-based informality index**	
Sample:	Historical kampung	BDD 200m
	(1)	(2)
Panel A: Access		
Road accessible by car (1=no)	0.81***	0.78***
	(0.05)	(0.09)
Paved road (1=no)	0.34	0.39
	(0.26)	(0.85)
Unpaved road (1= yes)	0.09	0.54*
	(0.13)	(0.28)
Damaged road pavement (1=yes)	0.10	-0.17
	(0.08)	(0.16)
Garden (1=no)	0.32***	0.20**
	(0.05)	(0.08)
Panel B: Neighborhood appearance		
Exposed wires (1=yes)	0.41***	0.37***
	(0.04)	(0.07)
Drainage canals (1=no)	0.25***	0.31**
	(0.06)	(0.14)
Trash (1=yes)	0.26***	0.48***
	(0.05)	(0.11)
Panel C: Permanence of structures		
Unfinished buildings (1=yes)	-0.23***	-0.10
	(0.08)	(0.13)
Permanent wall (1=no)	0.88**	-1.04**
	(0.35)	(0.46)
Unfinished wall (1=yes)	0.50***	0.52***
	(0.03)	(0.09)
Non-permanent wall (1=yes)	0.36***	0.33***
	(0.04)	(0.07)
Damaged wall (1=yes)	0.23***	0.15**
	(0.04)	(0.07)
Permanent fence (1=no)	0.09*	-0.04
	(0.05)	(0.08)
Rust (1=yes)	0.22***	0.20
	(0.05)	(0.14)
N	5277	1036
R-Squared	0.60	0.66
Distance	Y	Y
Topography	Y	Y
Landmarks	Y	Y
Distance to KIP boundary	N	Y
Geography FE	Locality	KIP boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports regressions at the pixel level where the dependent variable is the rank-based informality index and the regressors are the individual components of the attribute-based informality index. Column 1 includes the historical kampung sample and column 2 includes the boundary sample. Standard errors are clustered by locality in column 1 and by KIP boundary in column 2.

Other building height outcomes

Table A3 repeats the building heights analysis for different height outcomes. We discuss the historical kampung sample results (odd columns). The conclusions are similar for the boundary sample (even columns). In columns 1 and 2, we consider the number of floors for the tallest building in the pixel, finding an effect of -1.61 floors, relative to a control group mean of 5 floors. In columns 3 and 4, the dependent variable is the log of height; we obtain an effect of -19 log points (-21%, implying an effect size of 1.1 floors).

Table A3: Robustness checks for building heights

Dependent variable:	**Building Heights**		**Log(height)**	
Sample:	Historical kampung	BDD 200m	Historical kampung	BDD 200m
	(1)	(2)	(3)	(4)
KIP	-1.61***	-1.28**	-0.19***	-0.11**
	(0.37)	(0.58)	(0.04)	(0.05)
N	5277	1036	5061	1008
R-Squared	0.32	0.54	0.37	0.56
Distance	Y	Y	Y	Y
Topography	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y
Distance to KIP boundary	N	Y	N	Y
Exclude photos outside pixel	N	N	N	N
Replace photos outside pixel	N	N	N	N
Geography FE	Locality	KIP boundary	Locality	KIP boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports specifications similar to those in Table 2. Standard errors are clustered by locality in odd columns and by KIP boundary in even columns.

Assessing displacement across quintiles

Table A4 reports heterogeneous effects across quintiles of our land index to assess potential KIP-induced displacement of development activity across areas with different real estate potential. This is analogous to the heterogeneity analysis reported in the paper (see Figure 3 and Table 7), which includes hamlet fixed effects. Here, we only include locality fixed effects as we want to compare the estimates by quintile for KIP and non-KIP (the non-KIP coefficients will be omitted with hamlet fixed effects since the quintiles are defined by hamlets).

P-values reported at the bottom indicate that formal tests reject that KIP areas in Q1 are more developed (i.e. have higher land values and building heights) than non-KIP areas in Q2. This pattern is suggestive of KIP-induced displacement of development activity from high- to low-real estate potential areas, although it is in general challenging to quantify the extent to which our local effects reflect mere reshuffling.

Table A4: Heterogeneous effects by quintiles of land index

Dependent variable:	**Log land values**	**1(Height>3)**
	(1)	(2)
KIP X Quintile 1	-0.59***	-0.13***
	(0.11)	(0.03)
KIP X Quintile 2	-0.46***	-0.11***
	(0.06)	(0.02)
KIP X Quintile 3	-0.20***	-0.10***
	(0.05)	(0.02)
KIP X Quintile 4	-0.09*	-0.05***
	(0.05)	(0.01)
KIP X Quintile 5	0.16***	-0.06***
	(0.06)	(0.01)
Quintile 1	1.60***	0.10***
	(0.07)	(0.04)
Quintile 2	1.24***	0.06**
	(0.05)	(0.02)
Quintile 3	0.89***	0.03
	(0.04)	(0.02)
Quintile 4	0.47***	-0.01
	(0.04)	(0.02)
N	19848	19518
R-Squared	0.80	0.22
p-val ($H_0 : \beta_{Quintile1KIP} \geq \beta_{Quintile2Control}$)	0.01	0.01
Distance	Y	Y
Topography	Y	Y
Landmarks	Y	Y
Geography FE	Locality	Locality

* 0.10 ** 0.05 *** 0.01
Notes: Standard errors are clustered by locality.

Other measures of the informality index

Table A5 shows that our conclusion that KIP areas are more informal remains unchanged when using different approaches, such as pooling the rank-based index values for the two research assistants (and adding a fixed effect for one of them), as opposed to averaging the two scores (columns 1 and 2), as well as examining the three domains of the attribute-based index separately. The dependent variables correspond to z-scores for each domain (standardized using the control group mean and standard deviation within each estimation sample): access (columns 3 and 4), neighborhood appearance (columns 5 and 6), and permanence of structures (columns 7 and 8). The individual attributes in each domain are those listed in Table A2.

Table A5: Effect of KIP on informality, other measures

Dependent variable:	**Rank-based index, pooling**		**Lack of access**		**Poor neighborhood appearance**		**Non-permanent structures**	
Sample:	Historical kampung	BDD 200m	Historical kampung	BDD 200m	Historical kampung	BDD 200m	Historical kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KIP	0.29***	0.38***	0.03	0.05	0.05	0.19**	0.06**	-0.004
	(0.05)	(0.12)	(0.03)	(0.05)	(0.04)	(0.08)	(0.02)	(0.04)
N	10554	2072	5277	1036	5277	1036	5277	1036
R-Squared	0.23	0.35	0.13	0.21	0.14	0.21	0.13	0.23
Distance	Y	Y	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y	Y	Y
Distance to KIP boundary	N	Y	N	Y	N	Y	N	Y
Geography FE	Locality	KIP boundary	Locality	KIP boundary	Locality	KIP boundary	Locality	KIP boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports specifications similar to those in Table 4. Standard errors are clustered by locality in odd columns and by KIP boundary in even columns.

How can KIP affect density?

Table A6 examines heterogeneity for the parcel and population density analysis (Table 5). We first investigate whether parcel and population density are higher in KIP areas because (i) non-KIP areas are formal with already assembled parcels; or (ii) KIP areas have a higher density of parcels and people as a direct effect of KIP. We find suggestive evidence of the latter when we examine parts of the city where neighborhoods have not yet formalized. In column 1, we consider parcel density and we restrict the sample to pixels in quintiles 4 and 5 of our predicted land values index. Our results are similar if we consider areas in the periphery as defined by the last tercile by distance to the Monument, where we know that the KIP effects on land values and building heights are insignificant. Column 2 restricts the sample to pixels that appear as kampungs as per our photo survey (rank-based index values greater than 1). Columns 3 and 4 repeat this analysis at the hamlet level, with the log of population density as an outcome. Across columns 1 through 4, where the control areas in the sample are less likely to have formalized with assembled land, we continue to find higher parcel and population density in KIP.

Next, columns 5 and 6 show that regular vehicular road grids tend to reduce the positive impact of KIP on parcel density by 8.23 to 9.47 parcels per pixel, significantly offsetting the direct effect of KIP on land fragmentation. From the KIP policy maps we manually code the dummy "Grid roads" to be equal to 1 in KIP pixels where the roads paved as part of KIP form a grid, identified by the presence of 90 degree angles and straight lines. Around 8% of KIP pixels in the full sample and 3% in the historical sample have a grid-like network of roads. Pixels with and without grids are comparable in terms of observables. Additionally, we also interact the "Grid roads" indicator with the share of KIP vehicular roads over total KIP-provided roads in the pixel ("Vehicular"), which we interpret as a proxy for the permanence of the grid. About 42% of KIP-provided roads are vehicular in the historical sample (48% in the full sample). An orderly, grid-like layout of blocks could reduce fragmentation by easing coordination failures (Fuller and Romer, 2014) and by encouraging spatially contiguous development (Baruah, Henderson and Peng, 2021). This is suggestive of the benefits of planning regular blocks ahead and consistent with Michaels et al. (2021).

Table A6: Heterogeneous effects for land fragmentation

Dependent variable:	Parcel density		Log population density		Parcel count	
Sample:	Q4 & Q5 sample	Informal sample	Q4 & Q5 sample	Informal sample	Historical kampung	Full sample
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	9.50***	9.53***	0.46***	0.28***	8.76***	11.70***
	(0.90)	(2.63)	(0.10)	(0.07)	(1.05)	(0.65)
Grid roads					-7.59**	2.33
					(3.33)	(2.11)
Grid roads x Vehicular					-8.23**	-9.47***
					(4.13)	(2.71)
N	28175	2307	811	762	11002	88859
R-Squared	0.52	0.74	0.52	0.55	0.51	0.33
Distance	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y
Geography FE	Hamlet	Hamlet	Locality	Locality	Locality	Locality

* 0.10 ** 0.05 *** 0.01

Notes: This table studies heterogeneous effects of KIP on parcel and population density. The sample restrictions for columns 1 to 4 are explained in the text above. Columns 5 and 6 examine the effect of grid-like road networks. We only include locality fixed effects for the full sample analysis given the limited amount of grid road networks. The share of vehicular roads is de-meaned, so that the coefficient on the treatment indicator corresponds to the average treatment effect, evaluated for the average level of this share. Standard errors are clustered by locality.

Pre-KIP population density Since the policy rule targeted areas with high population density, the higher density in KIP today is likely confounded by historically high population density before KIP. To assess this selection bias, we obtained historical population density from the 1961 Jakarta population census, which reports population count by localities. We matched 1961 localities to current ones using names and historical maps. We matched 8,139 pixels, or 74% of the 11,002 pixels reported in column 1 of Table 5. This is relatively high considering that not all of Jakarta was settled by 1961: at that time, the population was less than 3 million (relative to 10 million today) and the area was 577 square kilometers (87% of area today).

Table A7 first shows that pre-KIP density can indeed have persistent effects even today. Columns 1 and 2, which include coarse district fixed effects and no controls, demonstrate that the KIP effect on parcel density is higher (14.87 parcels) in areas with above median pre-KIP density versus areas with below median pre-KIP density (9 parcels). Crucially, the estimates become similar across the samples once we add our controls and locality fixed effects. Formally, we can reject the one-tailed test that 14.87 is less than 9.00 (p-value: 1.7%) but we cannot reject that 8.97 is less than 7.78 (p-value: 31.9%).

Following Oster (2019), we show that selection by unobservables is unlikely to be able to explain away the results. We first assess the relative importance of selection on observables versus unobservables, finding a ratio of 3, comfortably above the heuristic threshold of 1. We also implement a bias correction factor to adjust for selection on unobservables on the basis of what we estimate for selection on observables. Doing so reinforces our conclusion that KIP areas today have higher density, even after accounting for pre-KIP density. If anything, the correction suggests that our estimates are conservative.

Table A7: Historical population density

Dependent variable:	**Parcel density**			
	(1)	(2)	(3)	(4)
KIP	9.00***	14.87***	7.78***	8.97***
	(1.86)	(2.05)	(2.16)	(1.32)
N	4214	3925	4214	3925
R-Squared	0.19	0.19	0.45	0.48
Distance	N	N	Y	Y
Topography	N	N	Y	Y
Landmarks	N	N	Y	Y
Geography FE	District	District	Locality	Locality
1961 Density	Low	High	Low	High

* 0.10 ** 0.05 *** 0.01

Notes: Standard errors are clustered by locality.

Current amenities

Table A8 investigates differences in access to current amenities. Columns 1 through 4 focus on public amenities. In particular, the outcomes are log distance (from the pixel's centroid) to the nearest school, hospital, police station, and bus stop, all drawn from OpenStreetMap. There are no effects for schools and police stations. The 7% effect for hospitals translates to 70 meters (small relative to a mean of 1000 meters). The 31% for bus stops is equivalent to 258 meters (moderate relative to a mean of 835) but falls sharply to 8% in the full sample. Since our main results are similar in the full sample, the difference in distance to bus stops cannot explain our main result. This corroborates the discussion in World Bank (1995) that KIP accelerated the provision of amenities in treated neighborhoods, but that non-KIP kampungs converged as a result of broader economic growth in Jakarta.

By contrast, columns 5 and 6 show that KIP areas have fewer formal commercial developments, with 1 p.p. lower retail density and 4 p.p. lower office development density. The dependent variables measure the share of each pixel that has retail activity or office developments, respectively, according to the administrative database on land use patterns. This is in line with our findings of KIP neighborhoods having lower land values and shorter buildings and being less formal.

Table A8: Access to current amenities

Dependent variable:	Log distance to				Density	
	School	Hospital	Police	Bus Stop	Retail	Office
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Historical kampung						
KIP	0.05	0.07*	0.00	0.31***	-0.01***	-0.04**
	(0.06)	(0.04)	(0.04)	(0.05)	(0.00)	(0.02)
N	11002	11002	11002	11002	11002	11002
R-Squared	0.25	0.60	0.71	0.56	0.15	0.26
Panel B: Full Sample						
KIP	-0.02	0.03**	0.01	0.08***	-0.01***	-0.02***
	(0.03)	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)
N	88861	88861	88861	88861	88861	88861
R-Squared	0.51	0.78	0.87	0.85	0.25	0.40
Distance	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y

* 0.10 ** 0.05 *** 0.01

Notes: The dependent variables are log of distance of a pixel's center to the nearest school, hospital, police station, and bus stop (columns 1 through 4), and share of retail (column 5) and office development within a pixel (column 6). The sample includes 11,002 pixels in the historical kampung (Panel A) and 88,861 pixels in the full sample (Panel B). Standard errors are clustered by locality.

Robustness for boundary analysis

A potential concern with the boundary discontinuity exercise is that we may be picking up differences across administrative units, to the extent that KIP boundaries coincide with administrative ones. In Table A9 we mitigate this concern by showing that the effects of KIP at the boundary are similar when considering variation within the same administrative unit, as we control for locality fixed effects within a 500 meter distance band.

Next, Table A10 shows that the estimates are similar when excluding boundary segments that overlap with railways (7 boundaries, columns 1 and 4), waterways (43 boundaries, columns 2 and 5), or both (48 boundaries, columns 3 and 6). We consider contemporaneous railways and waterways as per Openstreetmap as well as historical ones from the maps we utilize for our infrastructural controls.

Finally, Table A11 considers different buffer distances ranging from 150 meters (the optimal bandwidth for land values as per Calonico, Cattaneo and Titiunik (2014)) to 500 meters. Once again, we find similar effect sizes with KIP areas having land values that are lower by 15 to 19 log points and a likelihood of having tall buildings that is between 6 and 9 p.p. lower. One concern that arises with the boundary discontinuity sample is contamination or spillovers between treatment and control areas. The stability of the estimates across the buffer distances suggests limited evidence of spatial externalities due to KIP, echoing our findings on a lack of spatial decay patterns (Figure 5).

Table A9: Boundary analysis with locality fixed effects

Sample:	**BDD 500m**			
Dependent variable:	**Log land values**		**1(Height>3)**	
	(1)	(2)	(3)	(4)
KIP	-0.15***	-0.14**	-0.09***	-0.09***
	(0.05)	(0.06)	(0.02)	(0.03)
N	2781	2715	3196	3196
R-Squared	0.81	0.86	0.27	0.34
Distance	Y	Y	Y	Y
Topography	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y
Distance to KIP boundary	Y	Y	Y	Y
KIP Boundary FE	Y	Y	Y	Y
Locality FE	N	Y	N	Y

* 0.10 ** 0.05 *** 0.01

Notes: This table reports specifications analogous to the boundary analysis in Table 2. Standard errors are clustered by KIP boundary.

Table A10: Boundary analysis, dropping boundaries coinciding to waterways and railways

Dependent variable:	**Log land values**			**1(Height>3)**		
	BDD	BDD	BDD	BDD	BDD	BDD
	200m	200m	200m	200m	200m	200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.17**	-0.12*	-0.13*	-0.08**	-0.12***	-0.11**
	(0.06)	(0.07)	(0.07)	(0.03)	(0.04)	(0.04)
N	1191	888	829	971	610	572
R-Squared	0.80	0.84	0.84	0.39	0.43	0.45
Distance	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y
Distance to KIP boundary	Y	Y	Y	Y	Y	Y
Drop Boundaries	Railways	Waterways	Both	Railways	Waterways	Both

* 0.10 ** 0.05 *** 0.01
Notes: This table reports specifications analogous to the boundary analysis in Table 2. Standard errors are clustered by KIP boundary.

Table A11: Boundary analysis, robustness to different distance bands

Dependent variable:	**Log land values**			**1(Height>3)**		
	BDD	BDD	BDD	BDD	BDD	BDD
	150m	300m	500m	150m	300m	500m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.19***	-0.18***	-0.15***	-0.06	-0.08***	-0.09***
	(0.07)	(0.06)	(0.05)	(0.04)	(0.03)	(0.02)
N	929	1991	2781	602	2295	3196
R-Squared	0.81	0.81	0.81	0.43	0.30	0.27
Distance	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y
Distance to KIP boundary	Y	Y	Y	Y	Y	Y

* 0.10 ** 0.05 *** 0.01
Notes: This table reports specifications analogous to the boundary analysis in Table 2. Standard errors are clustered by KIP boundary.

Endogenous sorting

Educational attainment Table A12 shows that the lower land values in KIP are unlikely to be driven by compositional differences in the resident population. We examine educational attainment and find that, if anything, individuals in KIP have slightly better rates of junior secondary and high school attainment. We report regressions at the individual level from the 2010 Population Census. The KIP dummy is equal to 1 for individuals residing in a hamlet that is in KIP for the majority of its area. The effects are 1 p.p. to 2 p.p. relative to control group means of 0.76 for junior secondary and 0.58 for high school completion, respectively. The differences are small or insignificant for college and years of schooling. The sample includes 4.9 million individuals above the age of 25, controlling for gender, 70 age dummies, and locality fixed effects, as well as distance and topography controls averaged at the hamlet level. Table A13 finds similarly higher educational attainment when restricting the sample to stayers only (defined based on the district of birth coinciding with the current district). Results are similar when defining stayers based on the district of residence 5 years prior.

Table A12: Educational attainment

Dependent variable:	**Junior Secondary**	**High School**	**College**	**Years of Schooling**
	(1)	(2)	(3)	(4)
KIP	0.01**	0.02**	-0.005	0.07
	(0.01)	(0.01)	(0.01)	(0.07)
N	4924774	4924774	4924774	4924774
R-Squared	0.11	0.10	0.06	0.13
Distance	Y	Y	Y	Y
Topography	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y
Gender FE	Y	Y	Y	Y
Age FE	Y	Y	Y	Y
Geography FE	Locality	Locality	Locality	Locality

* 0.10 ** 0.05 *** 0.01

Notes: This table reports individual level regressions using the 2010 Population Census, with educational attainment dummies (columns 1 through 3) and years of schooling (column 4) as the dependent variables. The sample and controls are described above. Standard errors are clustered by locality.

Table A13: Educational attainment for stayers

Dependent variable:	**Junior Secondary**	**High School**	**College**	**Years of Schooling**
	(1)	(2)	(3)	(4)
KIP	0.01**	0.02**	-0.003	0.08
	(0.01)	(0.01)	(0.01)	(0.07)
N	2136737	2136737	2136737	2136737
R-Squared	0.22	0.20	0.08	0.25
Distance	Y	Y	Y	Y
Topography	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y
Gender FE	Y	Y	Y	Y
Age FE	Y	Y	Y	Y
Born in the same district	Y	Y	Y	Y
Geography FE	Locality	Locality	Locality	Locality

* 0.10 ** 0.05 *** 0.01

Notes: This table reports specifications similar to those in Table A12, but restricting the sample to individuals above age 25 born in the same district of residence. Standard errors are clustered by locality.

Migration Table A14 examines migration patterns using regressions at the individual level from the 2010 Population Census. In column 1 the dependent variable is a dummy equal to 1 if the individual was not born in the same district of residence ("migrant by birthplace"). In column 2 the dependent variable is a dummy equal to 1 if the individual was not living in the same district of residence 5 years prior ("5-year migrant"). The dependent variable for columns 3 and 4 is years of schooling. Column 3 restricts the sample to migrants by birthplace, and column 4 restricts the sample to 5-year migrants. All columns include fixed effects for gender and age and locality fixed effects. Distance and topography controls are averaged at the hamlet level.

Here, we explore the concern that KIP areas have worse outcomes due to the endogenous sorting in of negatively selected migrants. Instead, we find that KIP areas are less likely to have birth migrants and five-year migrants (columns 1 and 2) and that, if anything, migrants have more education (columns 3 and 4).

Table A14: Migration

Dependent variable:	**Migrant by birthplace**	**5-year migrant**	**Years of schooling**	**Years of schooling**
	(1)	(2)	(3)	(4)
KIP	-0.02***	-0.01***	0.03	0.11
	(0.005)	(0.003)	(0.08)	(0.09)
N	8621849	7861339	2788037	339213
R-Squared	0.14	0.06	0.10	0.11
Distance	Y	Y	Y	Y
Topography	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y
Gender FE	Y	Y	Y	Y
Age FE	Y	Y	Y	Y
Migrant by birthplace	N	N	Y	N
5-year migrant	N	N	N	Y
Geography FE	Locality	Locality	Locality	Locality

* 0.10 ** 0.05 *** 0.01
Notes: Standard errors are clustered by locality. Samples and dependent variables are reported in the text above.

Household sizes, fertility, and mortality Table A15 shows that there are no systematically different patterns in KIP with respect to household size, mortality, and fertility. Column 1 is analogous to the population density specification of column 3 in Table 5, with the dependent variable being the average household size in a hamlet. The next two columns present individual-level specifications similar to Table A14, but the sample is restricted to ever-married women who are over 10 years old and have ever had a live birth (columns 2 and 3).

Table A15: Differences in household size, mortality, and fertility

Dependent variable:	**Household size**	**Number of children deaths per 1000 live births**	**Number of children**
	(1)	(2)	(3)
KIP	0.01	0.13	0.02
	(0.03)	(0.68)	(0.01)
N	2533	2012188	2012188
R-Squared	0.34	0.03	0.24
Distance	Y	Y	Y
Topography	Y	Y	Y
Landmarks	Y	Y	Y
Age FE	Y	Y	Y
Geography FE	Locality	Locality	Locality

* 0.10 ** 0.05 *** 0.01

Notes: Standard errors are clustered by locality. Samples and dependent variables are reported in the text above.

Robustness to using the full sample

Table A16 investigates robustness to using the full sample for all the outcomes in Tables 2, 4, and 5. Here, we include hamlet fixed effects (except for population density which is defined by hamlets). The estimates are similar to those in the historical and boundary samples.

Table A16: Effect of KIP: Robustness to full sample

Dependent variable:	**Log land values**	**1(Height>3)**	**Rank index**	**Attribute index**	**Unregistered parcels**	**Parcel density**	**Log population density**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
KIP	-0.11***	-0.07***	0.28***	0.06***	0.03***	10.13***	0.48***
	(0.03)	(0.02)	(0.05)	(0.02)	(0.01)	(0.55)	(0.06)
N	19848	19518	7101	7101	88861	88861	2533
R-Squared	0.85	0.36	0.47	0.38	0.39	0.52	0.46
Distance	Y	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y	Y
Geography FE	Hamlet	Hamlet	Hamlet	Hamlet	Hamlet	Hamlet	Locality

* 0.10 ** 0.05 *** 0.01

Notes: The samples include 19,848 sub-blocks from the assessed land values dataset, 19,518 pixels for building heights, 7,101 pixels for informality indices from the photo sample, 88,861 pixels from the full grid of Jakarta and land parcels data, and 2,533 hamlets from the population census. All columns include hamlet fixed effects with the exception of population density (column 7) where locality fixed effects are used. Dependent variables are the log of assessed land values (column 1), the binary indicator for buildings above 3 floors (column 2), the rank-based informality index (column 3), the attribute-based index (column 4), the share of the pixel's area that has unregistered parcels (column 5), parcel count per pixel (column 6), and log of population density (column 7). The full set of controls are defined in Table 1. Standard errors are clustered by locality.

Other robustness checks: Selection bias for building heights

Below, we consider selection bias arising from development activity, stemming from the fact that the potential for building high-rises depends on zoning regulations and market access. In Table A17, we show that the results for building heights are similar if we drop pixels with no buildings (columns 1 and 2), restrict the sample to pixels in places that are zoned for commercial developments, based on digital zoning maps provided by the Jakarta City Government (columns 3 and 4), or restrict the sample to pixels that are within 1000 meters of a pre-determined historical main road, as a proxy of market access (columns 5 and 6). Our results are similar if we include all the observations but add controls for zoning and for being close to historical roads.

Table A17: Selection for building heights

Dependent variable:	**1(Height>3)**					
Sample:	Historical kampung	BDD 200m	Historical kampung	BDD 200m	Historical kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.12***	-0.08**	-0.13***	-0.08	-0.13***	-0.11**
	(0.02)	(0.03)	(0.04)	(0.15)	(0.02)	(0.04)
N	5081	1011	856	180	3617	691
R-Squared	0.29	0.38	0.44	0.63	0.31	0.40
Distance	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y
Distance to KIP Boundary	N	Y	N	Y	N	Y
Exclude no building pixels	Y	Y	N	N	N	N
Only pixels zoned for services	N	N	Y	Y	N	N
Only pixels near predetermined roads	N	N	N	N	Y	Y
Geography FE	Locality	KIP Boundary	Locality	KIP Boundary	Locality	KIP Boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports specifications similar to the heights analysis in Table 2. Standard errors are clustered by locality in odd columns and by KIP boundary in even columns.

Other robustness checks: Selection bias for assessed land values

One concern is that KIP areas are more likely to be informal today and property data for informal settlements are less likely to be reported. Table A18 investigates whether KIP areas are less likely to be represented in the assessed land values dataset. The unit of analysis is a pixel and the dependent variable is whether we observe an assessed value in the pixel. In contrast with the concerns above, we find a positive KIP coefficient, suggesting that KIP areas are if anything slightly over-represented in the data. Column 1 includes the full sample with hamlet fixed effects and column 2 restricts the sample to historical kampungs only, with locality fixed effects.

Table A18: Selection for assessed land values

Dependent variable	**1(Has assessed values)**	
Sample	Full sample	Historical kampung
	(1)	(2)
KIP	0.03***	0.04***
	(0.005)	(0.01)
N	88861	11002
R-Squared	0.09	0.09
Distance	Y	Y
Topography	Y	Y
Landmarks	Y	Y
Geography FE	Hamlet	Locality

* 0.10 ** 0.05 *** 0.01

Notes: Standard errors are clustered by locality.

Other robustness checks: Historical land institutions

In Table A19, we drop all hamlets that include Dutch settlement areas (identified as "built-up" in our historical maps), since the latter have historically had formal titles and are more likely to be high-quality today. Columns 1 and 2 show that our land values results remain the same even after dropping hamlets with Dutch settlements. Columns 3 and 4 present similarly robust findings for building heights. This also speaks to the concern of selection of development activity, as these areas are also more likely to have high market access.

Table A19: Robustness to excluding Dutch areas

Dependent variable:	**Log land values**		**1(Height>3)**	
Sample:	Historical kampung	BDD 200m	Historical kampung	BDD 200m
	(1)	(2)	(3)	(4)
KIP	-0.14***	-0.17**	-0.12***	-0.08**
	(0.05)	(0.08)	(0.02)	(0.03)
N	1885	730	5240	1010
R-Squared	0.72	0.83	0.29	0.38
Distance	Y	Y	Y	Y
Topography	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y
Distance to KIP boundary	N	Y	N	Y
Exclude hamlets with Dutch settlements	Y	Y	Y	Y
Geography FE	Locality	KIP Boundary	Locality	KIP Boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports specifications analogous to those in Table 2, excluding Dutch settlements indicated in our historical maps. Standard errors are clustered by locality except for the boundary analysis where we cluster by KIP boundary.

Other robustness checks: Standard errors

In Table A20, we demonstrate the robustness of our inference to alternative standard error specifications. We replicate the specifications in Table 2 and report the p-values corresponding to the KIP treatment effect. In our baseline historical kampung sample specification we cluster standard errors by locality, which has an equivalent-area radius of approximately 900 meters (column 1). In column 2, we consider a coarser level of clustering, the sub-district. There are 45 sub-districts in Jakarta, with an average area of approximately 15 square kilometers and radius of 2 kilometers. In columns 3 through 5, we employ the Conley (1999) GMM approach, allowing for arbitrary spatial correlation between observations within 700 meters, 900 meters (similar to the radius of our baseline clusters), and 1200 meters. P-values are very similar to our baseline ones. In addition, our boundary discontinuity inference - where we cluster by KIP boundary at baseline - is also robust to clustering standard errors at the sub-district level, with p-values of respectively 0.02 and 0.08.

Table A20: Effect of KIP on land values, building heights, and informality, standard errors robustness

	P-values of ATE				
Dependent variable	Cluster: locality (1)	Cluster: sub-district (2)	Conley, 700m cutoff (3)	Conley, 900m cutoff (4)	Conley, 1200m cutoff (5)
Log Land Values	0.00	0.00	0.00	0.00	0.00
1(Height>3)	0.00	0.00	0.00	0.00	0.00

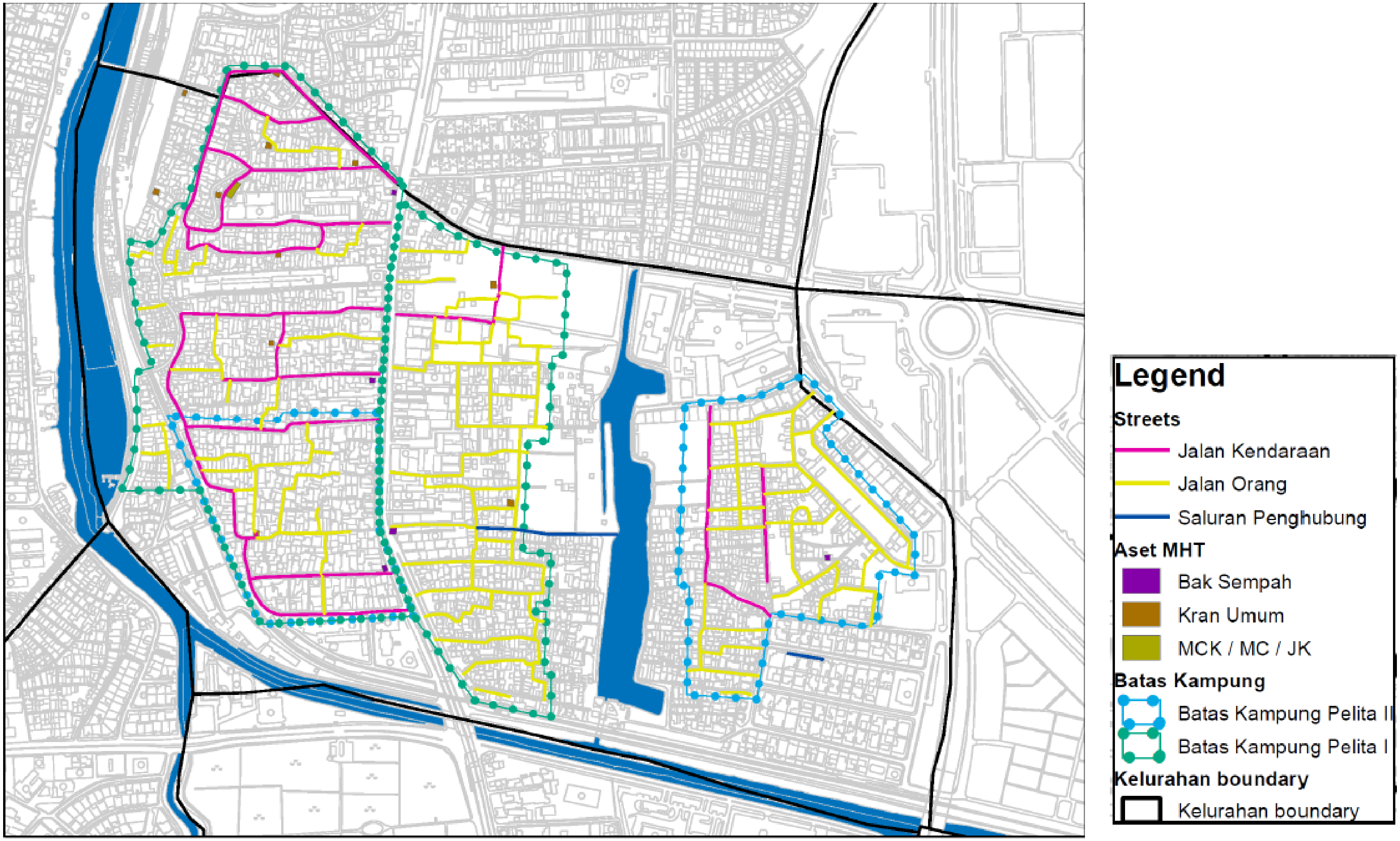
* 0.10 ** 0.05 *** 0.01

Notes: This table reports p-values for the significance of the treatment indicator. Each row corresponds to a regression. We replicate the specifications of Table 2, columns 1 and 3. In column 1 standard errors are clustered at the locality level (baseline). In column 2 we cluster at the sub-district level. In columns 3 through 5 we employ Conley (1999) standard errors with cutoffs of 700 meters, 900 meters, and 1200 meters respectively.

Appendix Figures

Figure A1: Kampungs in Jakarta, before and after KIP (Darrundono, 2012)

Figure A2: Policy maps: KIP assets

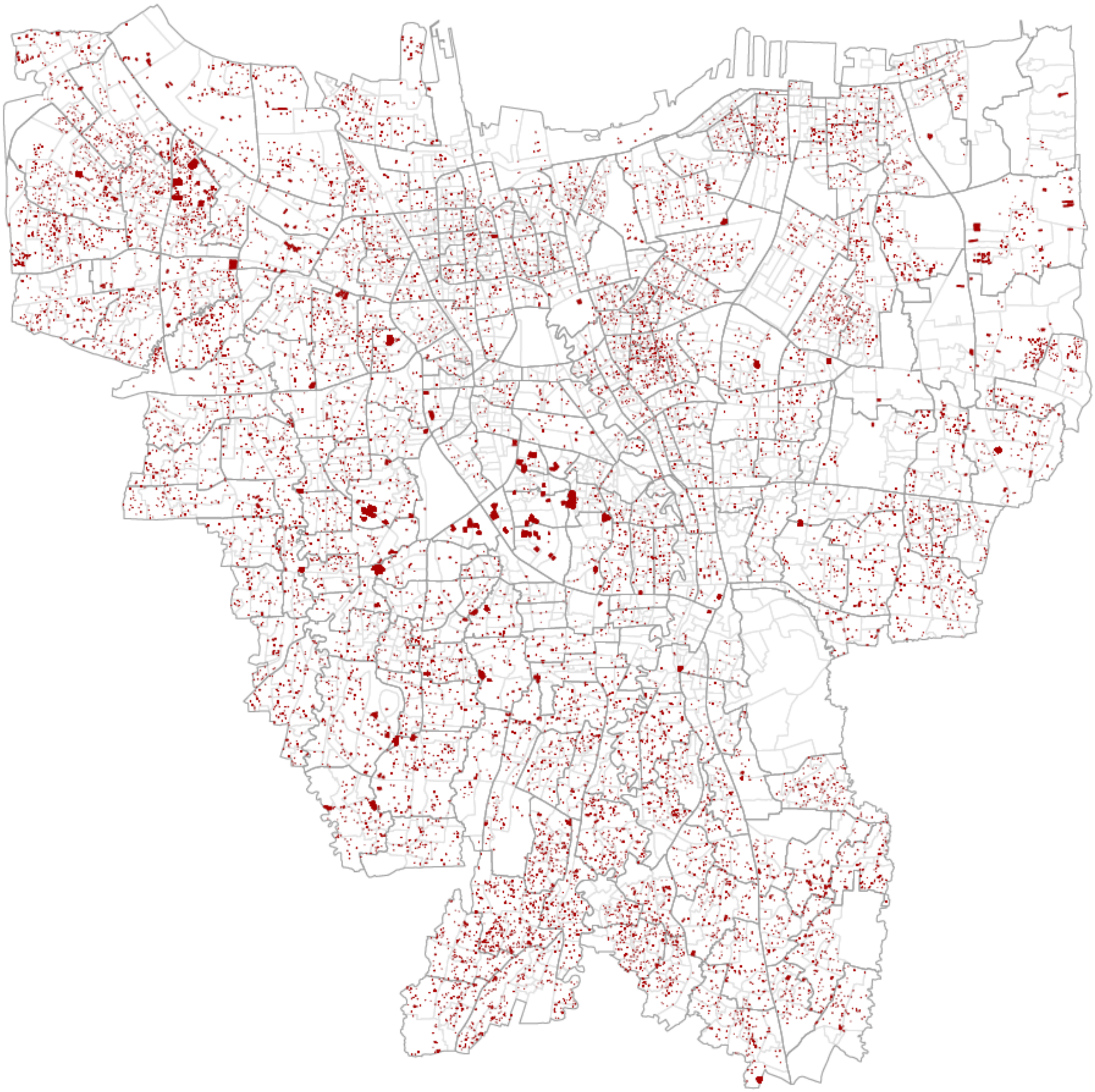


Notes: Map showing KIP assets. Dotted lines indicate boundaries of KIP areas, with different colors corresponding to different *Pelita* waves. Solid lines indicate vehicular roads (in pink), footpaths (yellow), and canals (blue). Dots denote public buildings.

Figure A3: Map of KIP boundary segments

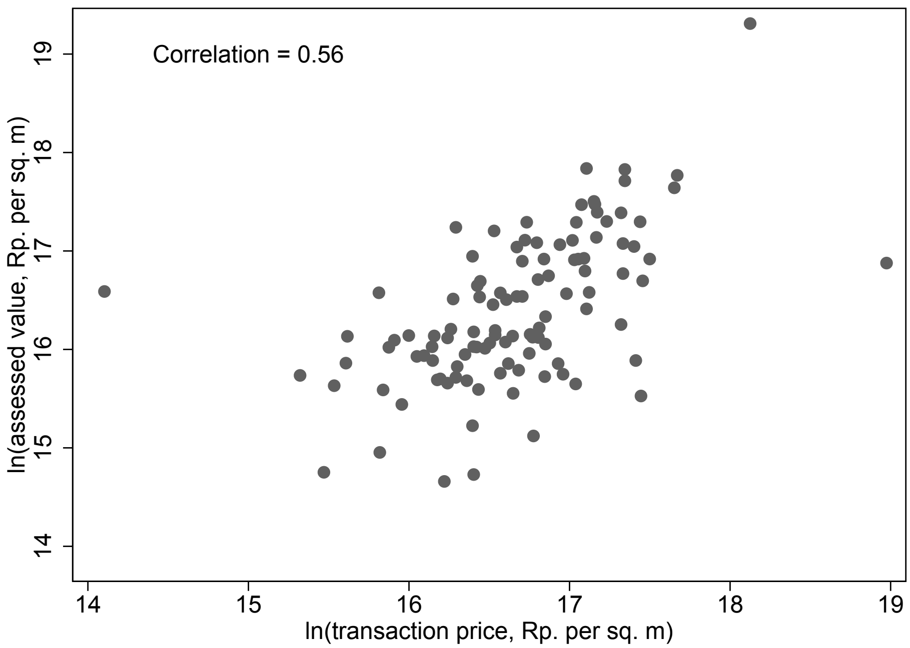
Notes: Map showing KIP boundary segments selected for the boundary discontinuity design.

Figure A4: Map of the assessed land values database



Notes: Map showing the coverage of the assessed land values database throughout Jakarta. Each shaded polygon corresponds to a sub-block. Thick boundaries correspond to localities. Light boundaries correspond to hamlets.

Figure A5: Scatterplot of assessed land values and transaction prices



Notes: This figure correlates the log of assessed land values and the log of transaction prices from www.brickz.id. Each point represents values averaged at the hamlet level.

Figure A6: Examples of coding of the rank-based informality index

0

1

2

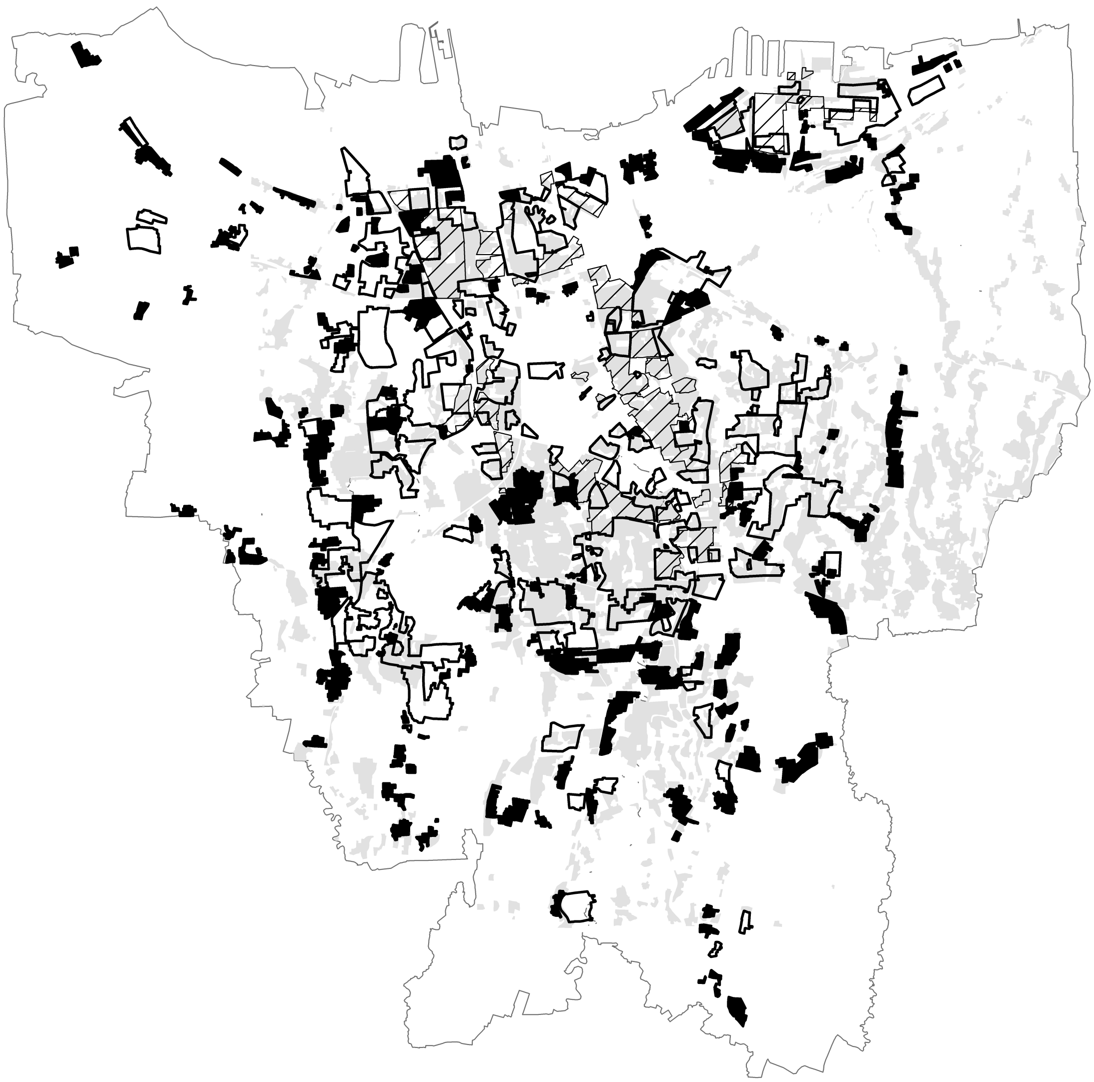
3

4

Figure A7: Example of cadastral map of land parcels

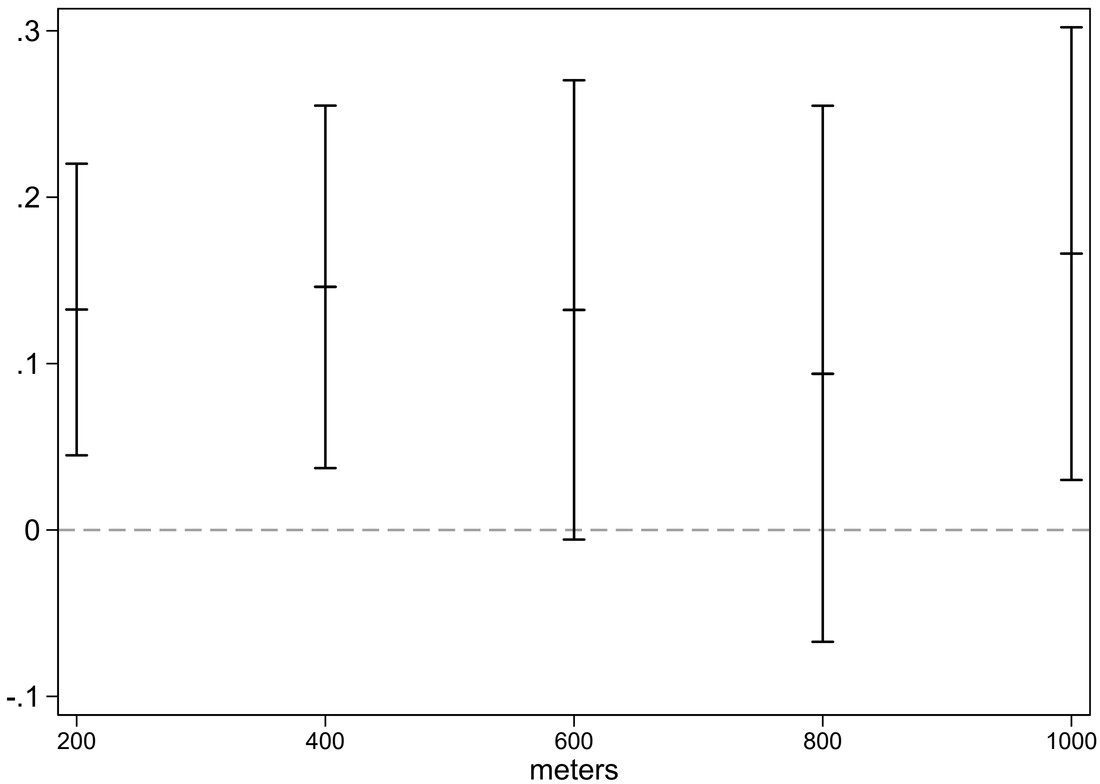
Notes: Cadastral map for one sub-district. The solid red boundaries indicate KIP treated areas.

Figure A8: Map of KIP waves



Notes: Map showing areas treated as part of the 3 KIP *Pelita* waves. Striped, hollow, and black areas were respectively exposed to KIP wave I, II, and III. Historical slums are shown in grey.

Figure A9: Spatial decay: Distance from high-density hamlet boundaries



Notes: We investigate the spatial decay pattern of land values away from the boundaries of 45 high-density, informal, and non-KIP hamlets. Specifically, these hamlets do not belong to KIP, have population density above the median, and appear as kampungs as per our photo survey (rank-based index values greater than 1). We estimate spatial decay patterns by exploring heterogeneous effects by distance bands. The omitted group is areas that are inside the 45 hamlets, and the key regressors include indicators for areas outside of the hamlet boundaries and within 200 meter distance bands. We start with 0 to 200 meters, and include up to 5 distance bands (800 to 1000 meters). We drop observations beyond 1000 meters and keep only non-KIP observations that are within 1000 meters. We include boundary pair fixed effects for the 45 hamlets, assigning all observations that are within 1000 meters from the closet hamlet boundary to belong to the same hamlet. Each point in the figure corresponds to a coefficient and 95% confidence interval for the distance bins regressors. We also compare the coefficient for the 0-200 meter distance band with the coefficient on KIP in Table 2, column 2. We reject the null hypothesis that these two coefficients are the same at the 1% level.

Data Appendix

Program boundaries

Our source for KIP program boundaries is a 2011 publication by the Jakarta Department of Housing (DPGP, 2011), consisting of more than 200 physical maps with a detailed indication of KIP boundaries as well as KIP investments. One of the goals of the publication was to make a detailed inventory of KIP investments in Jakarta. Extensive ground surveying was performed by the Jakarta Department of Housing mapping team to ensure accuracy. We were given access to the raw Autocad files that form the basis of these maps, achieving a 1:5000 meter scale or a resolution of 2.5 meters. These maps also detail the individual assets provided as part of KIP, including infrastructure (the network of vehicular and pedestrian road segments), sanitation facilities (garbage collection bins, public taps, public toilets, deep water wells, drainage canals), and community buildings (markets, health centers, and schools).

We employ this data source both to create our main explanatory variable - a binary indicator for whether a sub-block or a pixel falls within a KIP treated area - and for our boundary discontinuity exercise. Selecting boundary segments for the latter exercise involves an additional data processing step. If we restrict the sample to areas within 500 meters of KIP boundaries, some of the observations classified as control - i.e. on the non-KIP side - relative to one particular boundary segment may fall within the KIP side of a nearby boundary segment. We exclude contaminated units by manually selecting a subset of "clean" boundary segments, following Turner, Haughwout and Van Der Klaauw (2014). These boundary segments are displayed in Figure A3. We follow a similar procedure to select clean placebo boundaries for the test discussed in Section 8.1.

Market transactions

We compare assessed land values with real estate transaction prices scraped from the Brickz Indonesia website (www.brickz.id). Brickz has been collecting data of property sales since January 2015; sales are reported for properties advertised in the Rumah123 website (www.rumah123.com), an online property portal advertising sales and rentals. We scraped all the data available for sales of apartments and houses in Jakarta as of October 2016. For each entry, Brickz reports number of rooms, square footage, sale price and a street address, with varying precision. By a combination of Google API and manual search, we were able to geocode about 3800 entries at the street and street number level. In order to compare these data with assessed land values, we average transacted prices per square foot at the hamlet level.

Photographic survey

Sampling procedure In order to construct a representative sample of locations, we start from our grid of 75-meter pixels and select a random sample of 19,518 pixels, stratified by terciles of distance from the National Monument to ensure we have a broad spatial distribution. The proportion of pixels in the first, second and third distance terciles are respectively 50%, 40% and 10%. Within each distance stratum, we draw half of the observations from KIP and half from non-KIP areas. The proportion of KIP and non-KIP pixels in the original samples is comparable - about 45% KIP and 55% non-KIP. We code our main height outcome, a dummy for more than three floors (1(Height>3)) from this sample. Additionally, for a sub-sample of pixels in the historical and BDD estimation samples, we manually review the appearance of the photos further and code number of floors, the rank-based-, and the attribute-based informality index. We select 5,000 pixels from the historical kampung sample and 2,500 from the 500 meter BDD sample, resulting in 7,101 observations in total as a result of overlaps in the two sub-samples.

Photographs For each pixel, we first draw imagery from Google Street View. The Street View imagery was collected mostly in 2015-2017 (about 10% were collected in 2013). All locations for which Google could not return imagery were covered by our field enumerators. We provided them with latitude and longitude of the locations to be surveyed (corresponding to the center of pixels in the sample) and instructed to take four photographs from as close as possible to the exact coordinate points. We showed them photos from Google Street View as examples. They were asked to report GPS coordinates of the photos they took, so that the accuracy of the location could be verified. In a few cases the enumerators could not reach the exact location due to buildings, walls, or roads blocking the access. In these cases, we used the closest available photos from Google Street View. Results are similar if we only consider photos taken within 37.5 meters of the centroid of the pixel, and if we replace field photos taken outside of the pixel with photos from Google Street View that are closer to the intended location. These results are available upon request.

Building height To measure height at each surveyed pixel, we instructed our research assistants to count the number of floors of the tallest building within the pixel, as seen in the photos corresponding to each location. Occasionally, there would be tall buildings visible in the photos but located outside of the sampled 75-meter pixel, in which case they were not considered in the ranking. When uncertain, research assistants referred to Google Maps, where they would locate the dubious building and calculate the distance from the sampled location, thus determining whether it fell within or outside the pixel. For locations surveyed on the field, enumerators were instructed to consider only buildings within 75 meters of the location and provided with a rule of thumb of a maximum distance of 50 steps. For particularly tall buildings, the total number of floors was either not visible in the photo or not easy to count from the ground. In these cases, the dubious building was identified through Google Maps and the information on number of floors was either found on the building's website or obtained contacting the leasing office or concierge. For field locations with buildings of dubious height, enumerators entered the building and checked the number of floors from elevators.

Rank-based informality index We trained two research assistants, both from Jakarta, to independently rank photos on a scale ranging from 0 to 4. In particular, a value of 0 corresponds to areas that are completely formalized and comparable to a developed country city; 1 for neighborhoods that appear formal but retain some of the traditional features of kampungs, such as the narrow roads; 2 for kampungs that are overall in good conditions (e.g. they have paved roads and concrete buildings); 3 for kampungs that are in worse conditions and 4 for areas that are "very informal".

We performed an initial calibration of the index on a subset of photos and provided our research assistants with sample photos belonging to each category, explaining the characteristics that determined our assessment. When ranking locations, we instructed them to consider holistically the following aspects: width, paving, and condition of roads; density of structures; regularity of building heights; overall cleanliness of the neighborhood, including presence of rust, garbage, low-hanging electrical wires; quality and durability of building materials; irregularity of structures and presence of setbacks; size and quality of windows and doors. We also instructed our research assistants to focus on the physical appearance of the built environment and not on the activities of people, nor on the assets (such as parked cars) that may be visible in the photos.

Attribute-based informality index Our attribute-based slum index is based on the coding of fifteen attributes detailed below:

- Access:
  1. Is the location accessible by a four-wheeler (based on the width of roads/pathways): 1= no
  2. Presence of paved ground / road / footpath / access way: 1 = no
  3. Presence of unpaved ground / road / footpath / access way: 1 = yes
  4. Presence of damage to the pavement (e.g. sitting water, potholes) or incomplete paving: 1 = yes
  5. Presence of green space (e.g. garden, orchard): 1 = no. The latter attribute captures the fact that green space is not paved but does not imply a lack of accessibility.
- Neighborhood appearance:
  6. Presence of wires at building level: 1 = no

7. Presence of drainage canals: 1 = no
8. Presence of trash (uncollected garbage): 1 =yes.

- Permanence of structures:
   9. Presence of unfinished buildings (e.g. without roof, partially finished upper floors): 1 = yes
   10. Presence of permanent (concrete or brick) and finished (painted) walls : 1= no
   11. Presence of permanent but unfinished walls: 1 = yes
   12. Presence of non-permanent walls (wood or zinc): 1 = yes
   13. Presence of damaged wall (graffiti, peeling paint, holes): 1 = yes
   14. Presence of permanent fences: 1 = no
   15. Presence of rust: 1 = yes.

We standardize each attribute as a z-score and then average them in an index applying equal weights.

Land titles

In September 2020 we downloaded digital maps of Jakarta outlining land parcels and their registration status from the Bhumi webpage (*https://bhumi.atrbpn.go.id*), where geospatial data from the Ministry of Agrarian Affairs and Spatial Planning and National Land Agency is disseminated to the public. As a preliminary step, we removed from the shapefile polygons corresponding to areas that cannot be settled, such as roads, waterways, and large public parks, as visible in OpenStreetMap and Google Earth. We compute the share of land area of each pixel that we remove as part of this data cleaning process. Our results are robust to controlling for this share.

Control variables

At baseline we include eight landmark controls, capturing the distance, in logs, from a number of historical landmarks predating KIP. We consider the 1961 National Monument in Merdeka Square, the 1877 Tanjung Priok Harbor, and the location of the Old Batavia Castle (the earliest 17th century Dutch settlement). In addition, we include notable buildings from the 19th and 20th century corresponding to the parts of the city that appear to have the most economic activity based on the businesses, public buildings, and amenities listed in three historical maps we digitized (Visser Co te Batavia, 1887; Officieele Vereeniging voor Toeristenverkeer, Batavia, 1930; U.S. Army Map Service, 1959). These include the 1821 Concert Hall (later used as the Japanese headquarters during the occupation), the 1829 Hotel des Indes (at the core of the expat community where most embassies were), the 1932 Bioscoop Metropool (Jakarta's first mall, at the core of the historical shopping district), and the Akademi Nasional (which would host in 1949 the oldest private university in Jakarta) and Ragunan Zoo (opened in 1966), both located in suburban areas in South Jakarta.

We include four infrastructure controls: log distance from the main road arteries in the 1959 map (U.S. Army Map Service, 1959), log average distance to historical railway and tram stations (identified from maps from 1887, 1914, and 1935, (Visser Co te Batavia, 1887; Topographische Inrichting Batavia, 1914; Allied Geographical Section, 1935).) and the presence of historical wells or pipes within 1000m (identified from Smitt (1922)).

Our topography controls include slope and elevation, computed based on the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (NASA and METI, 2011), with a resolution of 30 meters.

We include four measures of local hydrology. Our first measure is the log average distance from waterways reported in the 1959 map (U.S. Army Map Service, 1959). Second, we include log distances from the coast and from the nearest permanent or semi-permanent water body, as reported by the European Commission Joint Research Centre's Global Surface Water Dataset (Pekel et al., 2016), a global 30 meter resolution raster map reporting the occurrence of water bodies from March 1984 to October 2015. We consider pixels corresponding to water for at least 50% of the sample period. Finally, we control for flow accumulation, a measure of exposure to flooding based on relative slopes: essentially, whether a location is downhill relative to nearby ones. Our choice of flood controls is motivated by Jati, Suroso and Santoso (2019), who finds slope, elevation, and flood accumulation are important topographic predictors of flooding in Java. We verify that they are strong predictors of flood damage in Jakarta, as measured by whether a hamlet is classified as "flood-prone" in OpenStreetMap.

From the entire sample of pixels, we dropped outliers for a few variables (flow accumulation, distance to the concert hall) in the balance table that resulted in 6 fewer observations in the sub-block level dataset and 145 fewer observations in the full pixel level dataset. The outliers were all above the 99th or below the 1st percentile.

Other variables

Boundaries of sub-city administrative divisions (localities and hamlets), as well as the location of roads are all drawn from OpenStreetMap.

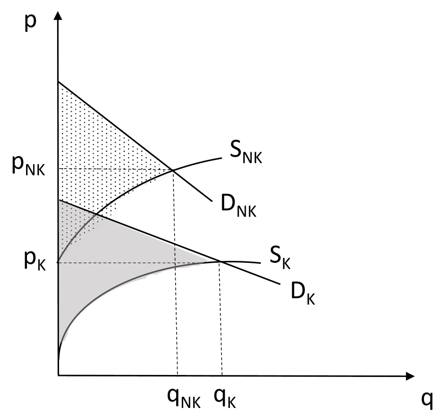
The cadastral maps we use to measure land fragmentaton are made available through the website of the Jakarta Regional Disaster Management Agency.

The Census data was obtained from the Harvard Library Government Documents Group.

Surplus Calculations

Below we provide details on the exercise in Section 7. We begin by illustrating our approach to characterize consumer and producer surplus in a hypothetical KIP neighborhood and its non-KIP counterfactual as a function of prices and quantities. Next, we discuss how we perform our calculations of these objects in Table 7 using our data and estimates. Finally, we discuss case studies of recent instances of kampung redevelopment through the lens of our framework.

Figure A10: Equilibrium in KIP and non-KIP neighborhoods



Surplus in the KIP and non-KIP equilibrium Consider the housing space (p,q) in a neighborhood, where q denotes quantities of built-up space and p denotes unit prices. D_K in the figure above represents housing demand in a KIP neighborhood. D_{NK} represents demand in a counterfactual without KIP. Similarly, S_K and S_{NK} represent housing supply in KIP and non-KIP respectively, with the two curves reflecting technological differences between building informally and formally (Henderson, Regan and Venables, 2020).

Our exercise considers surplus in a KIP neighborhood in today's Jakarta and its non-KIP counterfactual. The housing equilibrium under KIP is denoted by (p_K, q_K). The shaded region represents total surplus, including consumer (CS_K) and producer surplus (PS_K). The non-KIP counterparts are defined similarly and the corresponding surplus is the dotted region. Surplus is expressed relative to a minimal level of housing utility delivered at the edge of the city, which we normalize to 0.

We consider the difference in neighborhood surplus between the KIP and the non-KIP equilibrium, $CS_K + PS_K - (CS_{NK} + PS_{NK})$. Our exercise focuses on overall surplus to society abstracting from incidence considerations, including transfers between non-KIP and KIP consumers or producers, the surplus accruing to parties such as land assembly intermediaries or the government, and the distinction between landlords and tenants.

In order to calculate consumer surplus, we utilize a linear approximation for demand which we validate below. Denote the equilibrium prices and quantities as (p^*, q^*). We approximate the area below the demand curve using a triangle with base q^* (known) and height Dp (unknown), where Dp represents the difference between the vertical intercept of the demand curve and the equilibrium price p^*. Note that Dp represents the absolute change in p corresponding to a change in q from 0 to q^*, namely $Dq = q^*$. Denoting with ε the absolute value of the price elasticity of demand in (p^*, q^*) and applying the definition of elasticity with $Dq = q^*$ yields:

$$Dp = \frac{Dq}{\beta} \cdot \frac{p^*}{q^*} = \frac{p^*}{\varepsilon}.$$

Consumer surplus is thus calculated as:

$$CS = \frac{p^* q^*}{2\varepsilon}. \tag{B.1}$$

For producer surplus, we assume a Cobb-Douglas functional form for the housing supply curve $p = (Aq)^{\frac{1}{\delta}}$, where δ denotes supply elasticity (Combes, Duranton and Gobillon, 2021). We then integrate above the supply curve and below the equilibrium price as follows:

$$PS = p^* q^* - \int_0^{q^*} (Aq)^{\frac{1}{\delta} dq}. \tag{B.2}$$

Plugging $A^{\frac{1}{\delta}} = \frac{p}{q^{\frac{1}{\delta}}}$ from the supply curve in the above we obtain:

$$PS = p^* q^* - \frac{p^*}{q^{*\frac{1}{\delta}}} \left[\frac{\delta q^{*1+\frac{1}{\delta}}}{1+\delta} \right] = \frac{p^* q^*}{1+\delta}. \tag{B.3}$$

Neighborhood surplus in the KIP and non-KIP equilibria can be thus expressed as real estate values rescaled by elasticities:

$$Surplus_i = CS_i + PS_i = p_i q_i \left(\frac{1}{1+\delta_i} + \frac{1}{2\varepsilon_i} \right) \text{ for } i \in \{K, NK\}. \tag{B.4}$$

Empirical implementation For Table 7, we use our data and estimated treatment effects (columns 1 and 2) to provide a calculation of $p_K q_K$ (column 3), $p_{NK} q_{NK}$ (column 4), $p_K q_K - p_{NK} q_{NK}$ (column 5), and $Surplus_K - Surplus_{NK}$ (column 6) for individual neighborhoods (hamlets).

We consider all hamlets that have KIP presence and for which we observe land values and heights (569 hamlets in total) and we classify them by quintiles of our land index, based on non-KIP land values (see Section 5.3). For each hamlet, we observe average land values (v_K) and building heights (h_K) in KIP and utilize them to pin down real estate prices and quantities in the KIP equilibrium (p_K, q_K). We then leverage KIP treatment effects on land values and heights $\left(\widehat{\beta}_v, \widehat{\beta}_h\right)$ to construct the counterfactual non-KIP prices and quantities (p_{NK}, q_{NK}). Treatment effects are estimated for each quintile, from a regression on the full sample that includes our full set of controls and hamlet fixed effects. Rows 1 through 5 in Table 7 report averages of the objects above across hamlets within each quintile. Row 6 provides a weighted average across the five quintiles, weighing by the KIP land area in each quintile.

As a first step, we calculate pq (total value of real estate space) as a function of v (land values per square meter of land) and h (building heights in number of floors), which is what we measure in our data. Based on the assessment approach of the Indonesian Land Agency, the total value of real estate consists of two components: value of the land and value of the structures (buildings). Denoting the building footprint area as l and construction costs per square meter of built-up space as c, total real estate value in a plot of land with area L can be expressed as:

$$pq = v \cdot L + c \cdot h \cdot l. \tag{B.5}$$

In turn, l can be calculated as horizontal coverage ϕ (expressed as the share of a plot that is built up) multiplied by the total land area of the plot: $l = \phi \cdot L$. Dividing by L, we calculate $p_K q_K$ in USD per square meter of land (column 3) in each location as:

$$\widehat{p_K q_K} = \left(\overline{v_K} + c_K \cdot \overline{h_K} \cdot \phi_K \right) \tag{B.6}$$

where $\overline{v_K}$ and $\overline{h_K}$ are, respectively, the average land values (in USD per square meter) and building heights (in number of floors) observed in KIP areas within the hamlet, c_K is an estimate of construction costs (in USD per square meter of built-up space) in kampungs, and ϕ_K is the average share of a 75-m pixel that is occupied by buildings in KIP areas. All dollar amounts are expressed in 2015 USD, at an exchange rate of 13,830 Rupiahs to dollars.

In order to estimate the implied non-KIP counterpart, $p_{NK}q_{NK}$ (column 4), we utilize our estimated treatment effects to calculate the counterfactual land values and building heights. This yields:

$$\widehat{p_{NK}q_{NK}} = \left(\overline{v_K} \cdot e^{-\widehat{\beta_v}} + c_{NK} \cdot \overline{h_K} \cdot e^{-\widehat{\beta_h}} \cdot \phi_{NK}\right) \tag{B.7}$$

where c_{NK} is an estimate of construction costs in formal areas, ϕ_{NK} is the average built-up land share in non-KIP areas, and $\widehat{\beta_v}$ and $\widehat{\beta_h}$ are the KIP treatment effects on log land values and log heights.

We set $\phi_K = 0.35$ and $\phi_{NK} = 0.18$, reflecting the built-up coverage we observe in KIP and non-KIP areas in our cadastral maps; these values are similar across different parts of the city. This is in line with the patterns documented by Henderson, Regan and Venables (2020) in Nairobi, with greater coverage in informal areas (between 40% and 60% in central areas) than in formal ones (20-30%). Our conclusions do not change when employing these alternative coverage values.

Finally, we calculate the difference in surplus (column 6) as:

$$\triangle\widehat{Surplus} = \widehat{p_K q_K}\left(\frac{1}{1+\delta_K} + \frac{1}{2\varepsilon_K}\right) - \widehat{p_{NK}q_{NK}}\left(\frac{1}{1+\delta_{NK}} + \frac{1}{2\varepsilon_{NK}}\right). \tag{B.8}$$

The key external parameters we bring in are $(\delta_i, \varepsilon_i, c_i)$, with $i = \{K, NK\}$. We set supply elasticity as δ_{NK} = 1.4 and $\delta_K = 1.3$, based on the formal and informal elasticities estimated for Nairobi by Henderson, Regan and Venables (2020). We set (absolute) housing demand elasticity in non-KIP ε_{NK} as 0.2, in the median range of the estimates provided by Malpezzi and Mayo (1987) for developing countries, all of which are based on formal sector data. Absent explicit estimates of informal housing demand elasticity, we assume that KIP and non-KIP consumers, plausibly lower- and higher-income respectively, have comparable compensated elasticity but differ in their uncompensated elasticity due to differences in the housing budget share. Indonesian household survey data (Badan Pusat Statistik, 2008) indicates that the housing budget share is slightly larger for richer households (0.17 versus 0.13). By the Slutsky equation, assuming unit income elasticity, the uncompensated elasticities should differ by 0.04. We thus set $\varepsilon_{NK} = 0.16$.

Our result of KIP being inefficient mainly in Q1 and Q2 does not depend on our particular choices of elasticities. We probe the robustness of our conclusions to our choice of informal demand elasticity by considering alternative values for the difference in housing budget shares, in the ranges reported by Balboni et al. (2020) for other developing countries. In order to overthrow our results, informal demand elasticity would have to be half the formal one, which would imply much larger differences in budget shares than those observed.

For supply elasticity, we consider 1.8 based on Heblich, Redding and Sturm (2020) estimates for 1800's London, which is in the range of the values found by the US literature (Saiz, 2010), between 1.2 - 2.6. We also consider a perfectly inelastic informal supply curve, whereby slums can only deliver two-floor housing (consistent with the bunching pattern we see in our heights data). None of these alternative specifications affect our conclusions.

We draw on on industry reports (ARCADIS, 2019) to set formal construction costs per square meter (c_{NK}) as \$1016 in quintiles 1 and 2, \$738 in quintile 3, and \$422 in quintiles 4 and 5. Specifically, we take the midpoints of the reported ranges of construction costs for Jakarta for the categories "apartments, high rise, high end", "apartments, high rise, average standard", and "terraced houses, average standard". Qualitatively, our results are similar if we employ the median value of \$650 for all quintiles. Lacking comprehensive data on construction costs in kampungs, for c_K we back out the ratio between average formal and informal construction costs implied by the difference in supply elasticities, which suggests informal costs equal to 30% of formal ones, or \$195 per square meter. This is in line with figures reported in architecture publications such as Nurdini, Yovita and Negri (2017) and the popular press.

Linear demand validation To probe the plausibility of our assumption that demand is approximately linear, we conduct a reduced-form exercise to asses whether the slope of the demand curve (Dp/Dq) in different points is comparable, leveraging heterogeneity across different parts of the city. From B.6, Dp/Dq can be calculated as a function of Dv/Dq. We then utilize KIP as a shifter of q and calculate Dv/Dq at different quintiles of distance from the city center as $(Dv/DKIP)/(Dq/DKIP)$, where we leverage heterogeneous KIP treatment effects on land values and heights. We thus obtain estimates of Dp/Dq for different values of q. We find negative values that are all comparable in magnitude, which lends support to approximating demand using a constant slope function. Our results are similar if we consider quintiles of our land index.

Kampung redevelopment case studies We apply our framework to case studies of KIP areas that were slatted for clearance in 2015-2016. We searched the press and policy reports for accounts of kampung redevelopments in recent years and identified those occurring in areas where we could observe KIP land values and heights in our dataset. We performed the surplus calculations discussed above by assigning each location to a land index quintile based on the corresponding hamlet and considering KIP land values and building height averaged within a 1000 meter buffer. We highlight three examples that are well-documented and span different quintiles. Below we provide surplus calculations to assess the overall gains and losses associated with formalization along with qualitative accounts that document the challenges associated with sharing surplus with the original residents. The patterns are qualitatively similar for other examples we considered.

Surplus calculations for select kampung redevelopments

	(1)	(2)	(3)	(4)	(5)	(6)
	KIP treatment effects		*Value of built-up stock*		*ΔValue $_{K-NK}$*	*ΔSurplus $_{K-NK}$*
	Log land values	*Log heights*	*KIP*	*Non-KIP*		
(1) Kalijodo, (Q2)	-0.28*** (0.08)	-0.01 (0.05)	$1,224	$1,894	-$670	-$910
(2) Kali Pessangrahan, (Q3)	-0.14** (0.07)	-0.15** (0.07)	$838	$1,171	-$332	-$307
(3) Bukit Duri, (Q5)	0.10** (0.05)	-0.03 (0.08)	$764	$727	$38	$572

Notes: Columns 1 and 2 report regression coefficients and standard errors (in parentheses) for the effect of KIP on log land values and log number of floors across quintiles of our land index, using the full sample including our full set of controls and hamlet fixed effects. * 0.10 ** 0.05 *** 0.01. All figures in columns 3 through 6 are in 2015 USD per square meter.

Our calculations for Kalijodo (row 1), in North Jakarta (Q2), suggests large gains from formalization of $910 per square meter. Residents were unsatisfied with the relocation options. They were offered subsidized rental apartments (*rusunawa*) in the Marunda complex in a peripheral area 24 km away (Q5). To provide a bound for the consumer surplus loss of displaced residents, we calculate consumer surplus in Marunda utilizing average non-KIP prices and quantities in a buffer of 3000 meters and the informal demand elasticity ε_K. We find it is 46% of the consumer surplus in the origin, corresponding to a 54% reduction.[41]

Our calculations suggest moderate gains from formalization of $307 per square meter for Kali Pessangrahan (row 2) in West Jakarta (Q3). Interestingly, despite kampung dwellers having property titles, land sale negotiations with developers have been stalling since 2015 (Yuliani, 2020). Residents have claimed that the compensation offered to them was below market value, all while a corruption scandal has emerged involving the project's land acquisition committee (Saputra, 2020).

[41] We consider a 3000 meter buffer because we have few land value observations in the immediate vicinity of Marunda. Considering a 2000 meter buffer instead, we find even more extreme reduction in consumer surplus of 79%.

Finally, formalization of Bukit Duri (row 3) in South Jakarta (Q5) is associated with a loss of $572 per square meter. Hundreds of households were evicted and offered relocation to Rusunawa Pulo Gebang, located 16 km away, and Rusunawa Cipinang Besar Selatan, 6 km away (Budiari, 2016). We calculate consumer surplus at the two destinations using a similar approach as discussed above, based on averages of non-KIP prices and quantities within 2000 meters. The difference in consumer surplus relative to the origin is respectively +13% and -45%. Residents requested to be rehoused on site instead, but although a nearby rusunawa was planned the units were not ready. A subsequent class action eventually established a compensation of $1.3 million, or about 20% of the estimated real estate value of the cleared slum. This sum did not go to the residents directly but to the governor's party, who committed to using it towards the purchase of land for an on-site apartment complex (Aya, 2018).