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

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Abstract

Developing countries face massive urbanization and slum upgrading is a popular policy to improve shelter for many. Yet, preserving slums at the expense of formal developments can raise concerns of misallocation of land. We provide causal long-term impacts of the 1969-1984 KIP program, which provided basic upgrades to 5 million residents covering 25% of land in Jakarta, Indonesia. We assemble high-resolution data on program boundaries and 2015 outcomes to address program selection bias. On average, KIP areas today have lower land values, shorter buildings, and are more informal, per a novel photographs-based slum index. The negative effects are concentrated within 5km of the CBD. We develop a spatial equilibrium model to characterize where the welfare implications of KIP are the largest. Counterfactuals suggest 77% of the welfare effects from removing KIP stem from land in the center and highlight how to mitigate losses to displaced residents. **JEL Classifications: R14, R31, R48**

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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). 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 over foregone opportunity costs of land use from preserving slums at the expense of formal developments.

This paper deepens our understanding of slum upgrading and the spatial misallocation of land as cities grow out of informality. Our first contribution is to provide novel long-term causal impacts of KIP. Second, we assemble a uniquely rich dataset to capture prices, quantities, and quality in formal *and informal* housing markets, by combining administrative data and an innovative photographic survey. While KIP planners targeted slums in worse conditions in the 1960's, we address program selection bias using our rich data to implement credible research designs. Third, we develop a spatial equilibrium model to quantitatively assess *where* the welfare gains from KIP are the largest and *how* to minimize losses to residents who are displaced.

Our research designs center around high-resolution policy maps and granular outcomes from 2015 assessed land values, building heights, and informality from our photos. We begin with a comprehensive sample spanning the entire city and compare KIP and non-KIP locations within the same hamlet (comparable to U.S. census block groups). The average KIP effects are -11 log points for land values, -7 percentage points (p.p.) for the likelihood of having tall buildings (more than 3 floors), -9 log points for number of floors in a building. Second, we restrict the sample to historical kampungs that existed before KIP and compare treated ones with those that were not, within the same locality (comparable to U.S. census tracts). Finally, we employ a boundary

[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.

discontinuity design within 200 meters of KIP boundaries. The identifying assumption is that unobserved neighborhood quality is comparable across KIP boundaries, conditional on our controls and fixed effects.

Across all specifications, KIP areas have lower average land values and fewer tall buildings. The effects are large (at least 40% of the control group means). Moreover, we establish that KIP places are more informal today, by constructing novel metrics of informality, including a photos-based index that ranks location quality and administrative data on parcel density and land titles.

To shed light on where the impacts are the largest, we leverage the large scale of the program, which covers 25% of land in Jakarta spanning regions at different stages of urban development. Intuitively, the opportunity costs from staying informal are greater close to the city center where the potential gains from redevelopment are larger. We use distance to the CBD to classify Jakarta into center, middle, and peripheral regions using 5 kilometer wide-distance bands. Interestingly, the KIP effects are the largest in the center followed by the middle then periphery (-14, -10, and -9 log points for land values and -13, -6, and -4 log points for building heights). We test that building heights in central KIP regions are shorter than middle non-KIP regions, consistent with spatial displacement of development activity from the center to the middle.

We explore several factors underlying delayed formalization in KIP. Today, KIP areas have greater population density and more fragmented land as measured by parcel density. Using detailed maps of KIP investments, we investigate differential effects by the type and intensity of the upgrades, but cannot detect significant differences, in line with their 15-year projected useful life (Darrundono, 1997). These results survive a battery of robustness checks. First, we exploit the staggered roll-out of KIP across three waves to assess program selection bias. Unconditionally, we estimate a monotonic pattern with more negative impacts for the earliest wave, in line with the selection rule prioritizing kampungs in worse conditions. This pattern disappears in our main specifications, reinforcing our assumption that the selection bias is adequately accounted for by our granular fixed effects or by restricting the sample to historical kampungs only. Next, we consider persistence in historical conditions. 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. Pre-KIP population density still affects modern outcomes, but cannot explain away our results (Oster, 2019). We investigate several types of spatial spillovers by examining spatial decay patterns across a range of outcomes. We find suggestive evidence of spillovers across KIP boundaries, but the patterns are not significant enough to change our conclusions and would tend to attenuate our estimates.

Next, we develop a spatial equilibrium model to characterize the welfare implications of KIP. The model features an open city with two types of residents, high- and low-skilled, who choose where to live and work and how much housing to consume (Tsivanidis, 2023). There are two housing market segments, informal and formal. We assume that markets are well-functioning within each segment, but there are frictions associated with converting land from informal to formal. On the supply side, developers choose whether to supply informal or formal housing, subject to formalization costs, and how tall to build. Locations are differentiated by a bundle of type-specific amenities, housing costs, and formalization costs. There are endogenous amenities in the form of positive spillovers from the share of high-skilled neighbors. General equilibrium is defined by location choice, developer profit maximization, and housing markets clearing.

Through the lens of the model, wedges in land values and heights between KIP and non KIP arise from differences in location fundamentals (amenities and formalization costs). The model captures the concurrent mechanisms through which upgrading can preserve slums. For example, KIP upgrades and enhanced tenure security are captured by better informal amenities in KIP, which will lead to more land allocated to informal land use. At the same time, crowding in KIP slums could complicate land assembly and relocation, captured by higher formalization costs in KIP.

As we take the model to the data, for each non-KIP location, we construct a KIP counterpart so that the model-implied wedges in equilibrium prices and quantities match the reduced-form estimates above, with larger effects in the center. Under our identifying assumptions, these wedges are not driven by differences in unobserved location quality and the model compares each non-KIP location to a KIP counterpart that is identical except for the policy shock. We calibrate the model using a combination of our own estimates and those from the literature.

We then implement counterfactuals to quantitatively assess how KIP affects welfare. As a benchmark, we begin by reporting a city-wide welfare effect of 3.1% from removing the KIP shock in the entire city (i.e., all KIP locations inherit the same amenities and formalization costs of their non-KIP counterparts). Not surprisingly, the high-skilled gain (5%) as reduced formalization costs boost formal housing supply and lower rents. As more high-skilled move in, endogenous amenity spillovers attract even more high-skilled. At the same time, there are large welfare losses to the low-skilled (-2.1%): as the informal land supply shrinks, the poor are displaced to less desirable places, and informal rents rise.

Next, we turn to where the effects are the largest. Importantly, we establish that 77% of the aggregate welfare gains are associated with KIP locations in the center. The counterfactual which only removes KIP in the center (within 5km from the CBD) yields a welfare effect of 2.4%. Conversely, outside of the center (where half of the program area is), removing KIP results in negligible gains. We verify that this is driven by the larger wedges in land values and heights in the center and not from any mechanical effects due to difference in area weights. The model accounts for both direct and general equilibrium effects, including sorting, spillovers, and equilibrium price effects.

Quantitatively, the direct effects are the primary drivers of the overall impacts. Our conclusions are robust to various modeling choices and parameters.

Our last counterfactuals highlight the trade-offs a policy maker may consider when balancing equity and efficiency. First, a zoning reform bundling the removal of KIP in the center and a relaxation of height restrictions can preserve gains to the high-skilled while minimizing losses to the low-skilled, as it allows more high-skilled to access the center while displacing fewer low-skilled. Second, redistributing 5% of the formal land surplus from formalization to the low-skilled will result in both groups gaining.

Beyond Indonesia, our findings deliver lessons for policy makers considering whether and where to implement slum upgrading and, more broadly, how to accommodate urban growth. Our welfare analysis suggests that spatial misallocation is largely associated with KIP areas that are central. A sizable share of the KIP program area is outside the center and we find limited gains from removing KIP in those areas. Additionally, urban transformation has major distributional implications as the poor are often displaced without compensation. Our results highlight important equity and efficiency trade-offs associated with slum upgrading.

Our paper is related to several lines of research. In recent work on urban development under weak property rights, Henderson et al. (2020) and Gechter and Tsivanidis (2023) highlight misallocation and opportunity costs of land use in the context of slums in Kenya and India, respectively. We leverage the wide geographic scope of the KIP program and rich policy variation to characterize *where* the gains from removing KIP are the largest and *how* to mitigate losses for the poor.

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. We contribute policy lessons on slum upgrading, which is highly relevant for many cities with limited vacant land and resources to provide shelter at scale.[3]

Third, we add to the literature on the measurement of urban form through imagery (Glaeser et al., 2018).[4] Our informality indexes address the notoriously difficult problem of defining and

[3] Additionally, Libertun de Duren and Osorio (2020) find limited medium-term impacts associated with the Favela-Barrio slum upgrading program in Brazil. 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. The literature has also considered titling (Field, 2007, Galiani and Schargrodsky, 2010), public or subsidized housing (Picarelli, 2019, Barnhardt et al., 2017, Franklin, 2019, 2020, Kumar, 2021), and housing improvements (Galiani et al., 2017). Also see Brueckner and Lall (2015) and Marx et al. (2013) for an overview.

[4] Remotely-sensed imagery has been employed to map slums (Kuffer et al., 2016), but this approach misses many attributes visible from the ground. Imagery from Google Street View has been utilized in the United States (Naik et al., 2017), but it can be problematic in developing countries due to coverage bias.

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 presents our model and welfare discussion, Section 8 addresses identification threats and robustness, and Section 9 concludes.

2 Background

Indonesia is the fourth most populous country in the world with 274 million inhabitants (World Bank, 2021). Jakarta, the capital, has close to 11 million residents and is part of the sprawling metropolitan area of Jabodetabek (Haryanto, 2018),[5] the world's second-largest, home to 35 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. In Jakarta, it 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)). We consider the first three waves of KIP, implemented in Jakarta between 1969 and 1984.

The earliest upgrades to traditional settlements began in the 1920's with Dutch interventions. 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.

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

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 program improved access to kampungs by widening and paving roads, bridges, and footpaths. The second component was sanitation and water management, including public water supply and drainage canals to address flooding. Third, KIP provided community buildings such as primary schools and health clinics.

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 halted due to budget cuts following the 1986 oil shock. The roll-out prioritized kampungs in worse conditions. Planners created a scoring rule to rank kampungs based on physical characteristics (e.g. sanitation, flood damage, and road quality), kampung age, population density, and estimates of income (KIP, 1969). Given time constraints and limited information, the scoring rule over-weighted physical conditions that were easily observable. Moreover, kampungs had to be distributed evenly across Jakarta's five districts.

Prior reports on KIP. KIP is generally considered by practitioners and policy makers as a successful program (Devas (1981), Taylor (1987), World Bank (1995), Darrundono (2012)). A 1995 World Bank evaluation report concludes that KIP "improved the quality of life of Indonesian urban areas at a low cost of investment" (World Bank, 1995, p. 71).[6] The report highlights improvements in neighborhood conditions, residents' education and health, and private housing investments. 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.[7]

2.2 KIP and kampung redevelopment

The World Bank report recognizes that rising demand for urban land would eventually trigger the redevelopment of kampungs. Today's Jakarta provides an ideal setting to study the implications of slum upgradings in the long-run. The city faces an annual population growth rate of 1.7% (World Population Review, 2024) and a severe housing backlog, with an estimated 70,000 additional housing units needed each 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).

[6] The report is based on interviews and surveys of two KIP kampungs in the center and a non-KIP one in the periphery.

[7] 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).

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.[8] 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). Formally registering titles entails significant transaction costs, including high fees (8.5%), challenges in verifying tenure status and resolving disputes, and delays due to backlogged courts. 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.[9] In addition, assembling many contiguous land parcels in dense kampungs entails holdout problems (Brooks and Lutz, 2016).

Preserving slums is one of the inherent objectives of slum upgrading programs, as these areas give shelter to many residents. This occurs through a few potential channels. First, higher land values from the upgrades will increase redevelopment costs. Moreover, upgrades and non-eviction guarantees can make slums more attractive and strengthen residents' perceptions of their occupancy rights (Fox, 2014). This encourages them to stay, plausibly leading to greater population density and more fragmented land (as stayers sub-divide land parcels) over time. In turn, this can increase relocation 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).

3 Data

This Section discusses our primary data sources, including policy maps, land values, building heights, and our novel measures of informality. More details about data sources and processing

[8] In 2016 we conducted a field survey with 300 households in eight kampungs, with the local government's permission Wong (2019). 77% of houses had brick or concrete walls, 93% reported having metered electricity, 79% utilized private water supply, and 71% had private toilets. However, 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.

[9] Evictions without compensation are common (Human Rights Watch, 2006) and carried out by the government for public works or by developers (with the government's cooperation) for residential and commercial projects (Szumer, 2015). The law does not provide any monetary compensation to residents without a title (Obeng-Odoom, 2018). In practice, developers sometimes offer compensation through middlemen, but well below market value (Leitner and Sheppard, 2018). The government will occasionally offer subsidized rental apartments, mostly in peripheral areas, that residents are often unsatisfied with (Wijaya, 2016).

are provided in the Data Appendix. Table A1 reports summary statistics. Our database is uniquely rich, high-resolution, and with a comprehensive coverage of Jakarta.

3.1 Assessed land values

We observe assessed land values from a 2015 digital map available through the Smart City Jakarta initiative. The Indonesia land agency uses a property appraisal valuation model that relies on transactions and market data (e.g. from brokers and notary offices). The estimated property value is decomposed into a building component and a land component, which is what we consider. We have land values in Rupiah per square meter for nearly 20,000 sub-blocks (the smallest zoning unit), evenly distributed throughout the city (Figure A1). Importantly, in Jakarta, properties are transacted actively in both the formal and informal markets (Leaf, 1994). We verify that KIP areas are not underrepresented in the dataset.[10] 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. We validate our 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 property prices from Indonesia's largest property website, obtaining a correlation coefficient of 0.56 (see Figure A2).[11]

3.2 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.[12] We draw a representative sample of 19,515 pixels from the full Jakarta grid of 89,000 pixels, stratifying to ensure broad spatial coverage (details of the sampling procedure are in the Appendix). In each pixel, we obtain four photos from four angles.

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 too large for the narrow streets of some kampungs (8% of pixels) and cannot access private gated developments (2%). For these areas, we obtained photos from

[10] Pixels in the full sample are, if anything, 3% more likely to have an assessed land value observation. In the historical sample the percentage is 4%. Both are significant at the 1% level. See Table A15.

[11] This correlation is relatively high, since it is between land values and property values (which also includes the value of structures). To benchmark how correlated the two should be, we convert our land values into property prices using our own data on building heights and imputing the value of the structure. Our approach to convert land values to property values is used also for our model (Section 7) and is explained in Section B.2.1. We obtain a correlation of 0.60 between assessed land values and corresponding constructed property values, suggesting that 0.56 is fairly high.

[12] This is the area required for an average high-rise development, based on reports from the Jakarta City Planning Agency.

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).

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 them. We also consider log number of floors of the tallest building, for the (selected) sample of pixels that have at least one building.

3.3 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 19,515 pixels (approximately 78,000 photographs), we hand-coded a rank-based index that provides a holistic assessment of the neighborhood's quality. The index ranges from 0 (very formal) to 4 (very informal). Examples can be found in Figure A4. Research assistants 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).

Attributes-based index. To validate our holistic rankings, we construct an attributes-based index that quantifies fifteen attributes in three domains: vehicular access, neighborhood appearance, and the permanence of structures. Due to the complexity and heterogeneity of the imagery, we coded the attributes manually and for a subsample of 7,101 pixels. The resulting index takes higher values for locations with a higher than average degree of informality based on those attributes. The rank-based index is positively correlated (0.64) with the attributes-based one and with most of the individual attributes.

Titles. We observe what type of titles land parcels have from a unique digital land map 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.

Parcel density. We consider the number of parcels in each pixel based on digital cadastral maps created by the Jakarta Department of Housing in 2011 (Figure A10).

Household density. We draw upon the 2010 complete count Population Census to capture population density and demographics for 10 million individuals in Jakarta, including age, gender, educational attainment, and migration status.[13] We calculate household density per pixel using an administrative shapefile of Jakarta's population.

3.4 Policy maps and historical kampungs

KIP boundaries. 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 (e.g. roads, sanitation facilities, and community buildings). An example map is provided in Figure A9. Figure 1 displays KIP treated areas as unshaded polygons.

For our boundary discontinuity design, we develop an automated procedure to define KIP boundary segments and treated and (non-contaminated) control areas as follows. We overlay a fishnet of 500 by 500 meter grid cells on KIP boundaries and use it to arbitrarily subdivide them into boundary segments. We then assign a unique boundary identifier to each segment, which we use to define boundary fixed effects. For each observation, we calculate the distances to the nearest and second nearest boundary segment. We assign to the "control" group any observation that is (i) not in a KIP polygon; (ii) within 200 meters of the nearest boundary segment; (iii) at a distance greater than 200 meters from the second nearest boundary segment (to avoid contamination). Figure A6 shows that the resulting boundary segments are evenly distributed across Jakarta. The Appendix discusses additional details on the selection procedure and robustness using other distance cutoffs.

Historical kampungs. We identify areas that were kampungs before the implementation of KIP through two maps, 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 are the shaded regions in Figure 1.[14] We also use these maps to trace major historical roads.

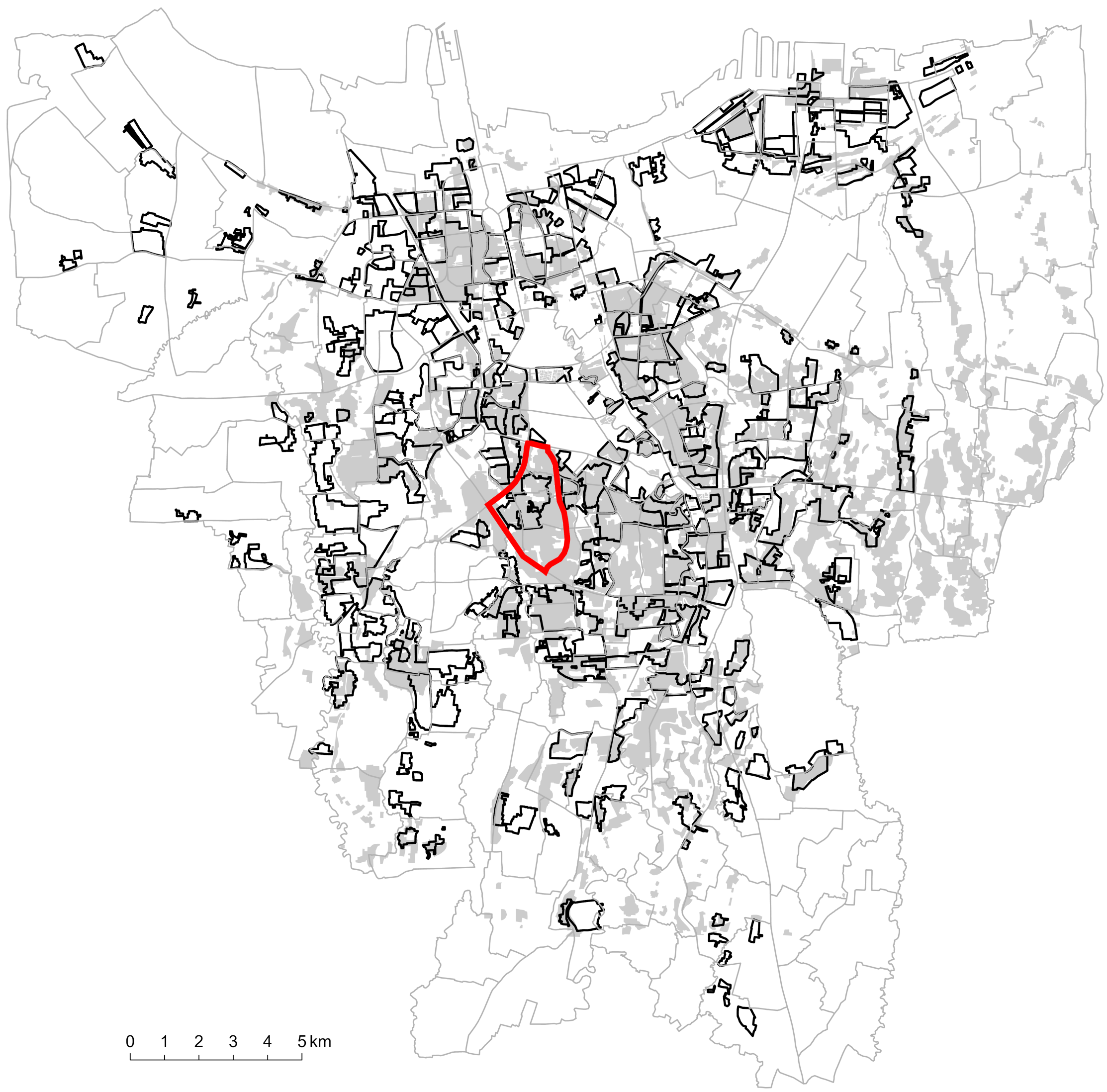
3.5 Descriptive analysis by distance to the CBD

Figure 2 presents scatter plots for the average land values and average number of floors by KIP status. The horizontal axis is distance to the CBD in kilometers. There is clear spatial decay away

[13]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 share 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 A13).

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

Figure 1: KIP boundaries and historical kampungs



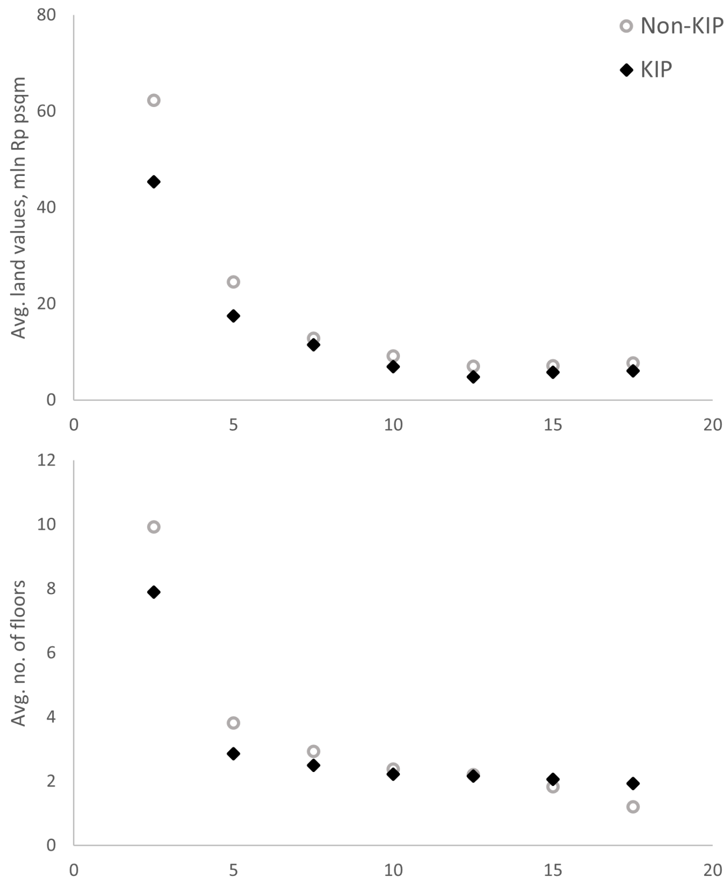
Notes: Map showing KIP boundaries (black border) and historical kampungs that existed before KIP (shaded regions). The grey borders are locality boundaries. The thick red boundary in the middle is the Golden Triangle.

from the center and a striking pattern of lower land values and building heights in KIP, with wedges that are larger closer to the center.

Definition of CBD. As CBD, we consider the "Golden Triangle" (red polygon in the map), an approximately 5 squared km area delineated by three road arteries. This area emerged as the modern CBD with the most skyscrapers (Bland, 2014).

Notably, KIP did not influence the location of the Golden Triangle. Even though skyscrapers emerged only several decades later, the roads delineating the Triangle were largely established

Figure 2: Land values and heights by KIP status and distance to the CBD



Notes: Average land values (millions of Rupiahs per squared meter) and average number of floors (inclusive of zeros) by KIP status and distance to the Golden Triangle (in kilometers).

before KIP, as the city prepared to host the 1962 Asian Games.[15] The notion that the Golden Triangle predates KIP is corroborated by the fact that there is significant KIP presence in this area (30% of the Triangle area), suggesting that skyscrapers did not emerge here as an attempt to avoid KIP areas.

[15]Ahead of the Asian Games, President Sukarno initiated the construction of a National Monument, and two major thoroughfares to the south of the Monument, Sudirman and Gatot Subroto. The Golden Triangle is enclosed by these two historical main roads and a third (Rasuna Said, which was inaugurated in the early 1970's). Our results are similar if we define the Triangle using the two historical roads that are pre-KIP and a straight line (in lieu of the third road).

4 Empirical framework

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

$$Y_{ij} = \alpha + \beta KIP_{ij} + \xi_{ij} + \varepsilon_{ij} \tag{1}$$

where unit i is a sub-block (for assessed land values) or 75-meter pixel (for heights) in neighborhood j, ε_{ij} is an idiosyncratic 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 ($E[\xi_{ij}|KIP = 1] - E[\xi_{ij}|KIP = 0] < 0$).

Our thought experiment involves two nearby locations (T and C) within the same neighborhood j. Unconditionally, T had a lower ξ_{ij} than C at the time of KIP, and was selected into KIP on the basis of the scoring rule. Over time, massive urbanization introduced large shocks to both T and C. Our identification assumption is that pre-KIP differences between T and C have a muted impact by today and that more recent shocks were common to T and C, so that T and C have similar quality today, conditional on observables and granular fixed effects. We discuss potential confounding due to program selection and persistent pre-KIP differences in Section 5.3 and 8.2.

Our first strategy utilizes the full sample spanning the city of Jakarta and includes more than 2000 hamlet fixed effects (comparable in area to U.S. census block groups).[16] Our identifying assumption is that hamlets are subject to common shocks and have uniform potential for redevelopment due to their small geographic area.

Our second strategy restricts the sample to historical kampungs that existed before KIP and includes around 200 locality fixed effects (the smallest jurisdiction where local taxes are collected, comparable in area to U.S. census tracts). This second strategy circumvents the concern that the full sample compares areas that were historically slums with areas that were not.

Third, we implement a boundary discontinuity design (BDD) comparing observations within 200 meters of KIP boundaries.[17] Our BDD specification controls for distance to the boundary interacted with KIP (similar to Michaels et al. (2021)), boundary segment fixed effects, and locality

[16] A list of all administrative units along with their area size is reported in Table A16 in the Data Appendix.

[17] As a reference, the optimal bandwidth à la Calonico et al. (2014) is 270 meters and 149 meters for log land values and for the height dummy, respectively. Because KIP polygons are relatively small, most KIP observations are within 500 meters from a KIP boundary. We address robustness to the choice of distance cutoff in Section 8.1.

fixed effects to address the fact that some of the boundary segments happen to be near administrative boundaries. Our identifying assumption is that, absent KIP, unobserved quality today would vary smoothly at the program boundaries, within these narrow distance bands.[18]

When estimating average treatment effects we show all three specifications. For our heterogeneity analyses and sample splits we primarily utilize the full sample due to lack of power in the other two sub-samples. Standard errors are clustered by locality except in the BDD where we cluster by boundary segment. Results are robust to using Conley (1999) errors to address spatial correlation (See Section 8.4.)

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, 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 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.[19] All variables are described in the Data Appendix.

Table 1 compares KIP and non-KIP areas to show that differences are negligible in our primary specifications. We report coefficients from regressing each of the controls on the KIP dummy, using the full sample and 2000 hamlet fixed effects (column 1), restricting to historical kampungs with 200 locality fixed effects (column 2) and in the 200 meter 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). [20]

[18]KIP neighborhood boundaries are pre-determined because they largely depend on hamlet boundaries defined during World War II by the Japanese for security purposes and likely uncorrelated with the potential for formal high-rises.

[19]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.

[20]Some of the coefficients are statistically but not economically significant. In the sub-block level dataset, column 2 (historical sample), KIP observation are 249 and 223 meters closer to Old Batavia castle (the colonial CBD) and to the Hotel des Indes (the center of the expatriate community), relative to a mean of 13 and 11 kilometers. In the pixel dataset, in column 4 (full sample), KIP observations appear closer to the old Harbor by 56 meters, relative to a mean of 14 km. In column 5 (historical) KIP observations are 111 meters further away from the Bioscoop Metropol (the city's first department store, relative to a mean of 6 km and 103 meters way from railway stations (3 km). These differences are insignificant in all other specifications.

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 Golden Triangle	-0.001	0.02	-0.002	0.03	-0.03	0.22
	[0.80]	[0.58]	[0.49]	[0.58]	[0.70]	[0.38]
Log Distance to Monument	-0.002	-0.02	-0.001	-0.001	0.01	-0.002
	[0.58]	[0.12]	[0.62]	[0.69]	[0.22]	[0.62]
Log Distance to Tanjung Priok Harbor	-0.0008	-0.004	-0.001	-0.004**	-0.002	-0.0006
	[0.66]	[0.67]	[0.68]	[0.04]	[0.46]	[0.75]
Log Distance to Old Batavia	-0.003	-0.02**	-0.05	-0.003	0.02	0.07
	[0.55]	[0.01]	[0.37]	[0.53]	[0.25]	[0.40]
Log Distance to Concert Hall	-0.002	-0.02	-0.002	-0.0002	0.01	-0.001
	[0.42]	[0.13]	[0.57]	[0.94]	[0.10]	[0.82]
Log Distance to Hotel Des Indes	-0.001	-0.02*	-0.002	-0.01	0.01	-0.02
	[0.66]	[0.09]	[0.58]	[0.29]	[0.39]	[0.29]
Log Distance to Bioscoop Metropool	-0.002	-0.01	-0.002	0.003	0.02**	0.002
	[0.60]	[0.55]	[0.67]	[0.28]	[0.03]	[0.80]
Log Distance to Akademi Nasional	-0.003	-0.03	0.01	0.001	-0.003	-0.0010
	[0.47]	[0.55]	[0.36]	[0.52]	[0.74]	[0.81]
Log Distance to Ragunan Zoo	0.003	0.01	0.0001	-0.00009	0.01	0.002
	[0.61]	[0.45]	[0.97]	[0.96]	[0.21]	[0.42]
Panel B: Infrastructure controls						
Log Distance to Historical Main Road	-0.01	-0.05	0.01	0.02	0.02	0.03
	[0.64]	[0.18]	[0.82]	[0.29]	[0.60]	[0.42]
Presence of Wells or Pipes within 1000m	-0.002	0.01	0.003	0.01	-0.01	0.01
	[0.74]	[0.24]	[0.74]	[0.30]	[0.50]	[0.36]
Log Average Distance to Railway Stations	-0.002	-0.02	-0.005	0.003	0.03**	-0.08
	[0.70]	[0.20]	[0.43]	[0.63]	[0.01]	[0.43]
Log Average Distance to Tram Stations	0.0006	-0.02	-0.01	0.003	0.02	-0.01
	[0.90]	[0.19]	[0.17]	[0.42]	[0.13]	[0.49]
Panel C: Topography controls						
Elevation, m	0.06	-0.58	-1.01	-0.04	-0.40	0.20
	[0.91]	[0.49]	[0.34]	[0.84]	[0.14]	[0.80]
Slope, Degrees	-0.23	-0.20	-0.54	-0.05	-0.12	-0.01
	[0.49]	[0.62]	[0.29]	[0.67]	[0.45]	[0.99]
Log Average Distance to 1959 Waterways	-0.0006	0.002	0.002	-0.0004	-0.003	0.002
	[0.69]	[0.77]	[0.41]	[0.64]	[0.26]	[0.25]
Flow Accumulation	0.54	0.92	1.23	0.24	0.39	0.53
	[0.24]	[0.13]	[0.18]	[0.35]	[0.20]	[0.54]
Log Distance to Coast	-0.002	-0.005	0.01	-0.002	-0.003	0.0002
	[0.59]	[0.75]	[0.55]	[0.55]	[0.61]	[0.98]
Log Distance to Surface Water Occurrence	0.01	-0.01	0.02	0.01	-0.01	-0.002
	[0.59]	[0.88]	[0.48]	[0.59]	[0.80]	[0.93]
N	19848	3144	4353	19515	5277	4138
Geography FE	Hamlet	Locality	KIP Boundary	Hamlet	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.

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 to 3). The dependent variable is the log price per square meter in a sub-block, from the assessed land values database. Column 1 reports the full sample specification and columns 2 and 3 present the historical kampung and BDD analyses, respectively. The full set of controls are listed in Table 1.

Across all three specifications, KIP areas have lower land values on average. The full sample estimate in column 1 shows that land values are lower in KIP areas by 11 log points compared to observably identical observations within the hamlet. Column 2 restricts the comparison to historical kampungs within the same locality, with an effect of -14 log points. Column 3 presents our BDD analysis showing a -18 log point estimate comparing observations within 200 meters of KIP boundaries. In Section 8.1, we show robustness and discuss threats related to spatial spillovers and confounding by coinciding boundaries. The confidence intervals overlap across all three columns.

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 3.2). Again, all three specifications indicate KIP areas have fewer tall buildings, with estimates ranging from 7 to 12 percentage points, and overlapping confidence intervals. These estimates are large (40 to 50 % relative to the mean). Figure A3 shows the distribution of building heights by KIP status, highlighting that non-KIP locations have more tall buildings and KIP locations have more short buildings.

On the intensive margin, we estimate an average KIP effect of -9 log points on number of floors (see Table A2). Translating our height effect into land values, we calculate that the lack of tall buildings in KIP explains 89% of the aggregate land value impact estimated in Table 2, column 1.[21] This exercise circumvents concerns around measurement error in informal KIP areas (by

[21] We estimate a hedonic regression using land values in non-KIP only and indicators for medium (4 to 10 floors) and tall (greater than 10) buildings. The omitted group represents buildings with three or fewer floors. We include standard controls for the heights specification, and hamlet fixed effects. Land values increase by 12 log points for medium-height buildings and 14 log points for tall buildings. We then apply the estimated price premium to impute the land value loss from having fewer tall buildings. KIP areas have 556 fewer buildings with more than ten floors. Combined with the 15% price premium in price per square meter, and assuming a building in each pixel, the total effect on building heights (expressed in land values) is US$6.3 billion. Similarly, we calculate that the effect for buildings between four and ten floors is US$3.9 billion. Therefore, the aggregate impact from the heights analysis is US$10.2 billion, which is 89% of the aggregate land value impact for the full sample (US$11.5 billion).

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

Dependent variable:	**Log land values**			**1(Height>3)**		
Sample:	Full Sample	Historical Kampung	BDD 200m	Full Sample	Historical Kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.11***	-0.14***	-0.18**	-0.07***	-0.12***	-0.10***
	(0.03)	(0.05)	(0.07)	(0.02)	(0.02)	(0.04)
N	19848	3144	4339	19515	5277	4128
R-Squared	0.85	0.73	0.84	0.36	0.29	0.53
Control Group Mean	15.84	15.89	15.80	0.18	0.24	0.21
Infrastructure	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	N	Y	N	N	Y
Geography FE	Hamlet	Locality	KIP Boundary	Hamlet	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, 2, and 3 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 full sample with 2058 hamlet fixed effects (303 with KIP variation). Column 2 includes the historical kampung sample with 196 locality fixed effects (87 with KIP variation). Column 3 uses observations within 200 meters from a KIP boundary, controlling for distance to the KIP boundary, and KIP boundary fixed effects (215 with KIP variation). Columns 4, 5, and 6 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 (full and historical specifications), and by KIP boundary (BDD specification).

using land values in non-KIP areas only) and overcomes sample coverage bias (by using heights data from a representative sample).

5.2 Heterogeneity by distance to the CBD

Next, we leverage the wide geographic scope of KIP to explore where the effects are the largest. As discussed in World Bank (1995), one concern is the upgrades can improve land values but also make slums more permanent than they otherwise would be. Once the gains from formalization are large enough to justify redevelopment, there can be a reversal in market outcomes as non-upgraded slums formalize. Intuitively, the KIP effects are most likely to be negative in areas with greater redevelopment potential, which we capture using proximity to the CBD.

While KIP covered a large area (110 square km), it is disproportionately in the center of modern Jakarta because KIP kampungs were settled early and the city has expanded outwards across the decades. We categorize Jakarta into central (pixels and sub-blocks that are 0 to 5km from the

Golden Triangle, inclusive), middle (5km to 10km), and peripheral (10km to 20km) regions.[22] Strikingly, 44% of the program area is in the center, relative to 43% and 13% in the middle and periphery.

We trace out the heterogeneous effects of KIP by distance to the CBD, utilizing the full sample and interacting the KIP dummy with indicators for the central/middle/peripheral regions (the omitted group is the non-KIP region in the periphery). We also add two indicators for the central and middle regions, in addition to hamlet fixed effects and our controls. We do not have enough power to detect heterogeneous effects with the boundary sample and the historical sample is too concentrated in the center.

The three interaction coefficients are identified from 303 hamlets that have variation in KIP status and are spread across Jakarta, with 34% of the hamlets in the center, 48% in the middle, and 18% in the periphery. As a reference, this breakdown is similar to the geographic distribution for the full sample of hamlets (31/41/28 %), except there is less KIP presence in the periphery.

We find patterns consistent with the scatterplots above (Figure 2). Column 1 of Table 3 presents larger KIP effects for land values in the center (-14 log points), compared to the middle (-10 log points) and periphery (-9 log points). Columns 2 and 3 present heterogeneous effects for the extensive and intensive margins of building heights using the photo sample of 19,515 pixels. The dependent variables are an indicator for buildings with more than three floors (column 2) and log of the number of floors (column 3, dropping pixels without buildings). Consistent with the plots above, we find taller buildings in non-KIP central locations (13 log points) relative to the middle (6 log points) and periphery (4 log points). The estimated effects for buildings above 3 floors are even (7, 7, and 6 p.p., respectively).

Potential displacement. While it is challenging to quantify the extent to which these spatial patterns reflect a mere reshuffling of buildings across neighborhoods, we provide some suggestive evidence of KIP-induced displacement of development activity away from central regions. We test and reject that KIP areas in the center have taller buildings than non-KIP areas in the middle. For example, focusing on column 3, relative to the periphery, building heights for KIP in the center are 17 log points shorter (sum of -0.13 and -0.04) but non-KIP in the middle are 4 log points (insignificant) shorter. This difference is significant at the 6% level. We find similar patterns when comparing the center and the periphery (4% p-value) as well as the middle and periphery (4% p-value).

These heterogeneity patterns are robust to a variety of approaches to rank neighborhoods by their formalization potential. For example, we constructed a predicted land index using non-KIP

[22] We pool the two outermost 5-km bins because only 5 % of KIP observations (195 obs) are beyond 15 km. Only 7 hamlets have within-KIP variation in the 15 to 20km bands.

Table 3: Heterogeneous effects by distance to the CBD

Dependent Variable	Log land values	1(Height>3)	Log height
	(1)	(2)	(3)
KIP X Center	-0.14**	-0.07***	-0.13**
	(0.06)	(0.02)	(0.06)
KIP X Middle	-0.10**	-0.07***	-0.06**
	(0.05)	(0.02)	(0.03)
KIP X Periphery	-0.09**	-0.06***	-0.04
	(0.04)	(0.02)	(0.03)
Center	0.30**	-0.01	-0.04
	(0.12)	(0.05)	(0.10)
Middle	0.09	-0.02	-0.04
	(0.07)	(0.02)	(0.05)
N	19848	19515	17233
R-Squared	0.85	0.36	0.41
p-val $(H_0 : \beta_{\text{Center, KIP}} \geq \beta_{\text{Middle, Control}})$	.80	.08	.06
p-val $(H_0 : \beta_{\text{Center, KIP}} \geq \beta_{\text{Periphery, Control}})$	.91	.05	.04
p-val $(H_0 : \beta_{\text{Middle, KIP}} \geq \beta_{\text{Periphery, Control}})$	.44	.001	.04
Control Group Mean	15.80	0.18	0.92
Infrastructure	Y	Y	Y
Topography	Y	Y	Y
Landmarks	Y	Y	Y
Geography FE	Hamlet	Hamlet	Hamlet

* 0.10 ** 0.05 *** 0.01

Notes: This table extends the full sample specifications in Table 2 which includes more than 2000 hamlet fixed effects and baseline controls. The key regressors interact the KIP indicator with indicators for central/middle/peripheral regions, defined respectively using 0 to 5km, 5 to 10km, 10 to 20km bands from the CBD. We also include one indicator each for the central and middle regions. In column 1 the dependent variable is log assessed land values for sub-blocks. The coefficient for the *Center* is identified using 44 hamlets (out of 666 in the center) with within-hamlet variation. The coefficient for *Middle* is identified using 88 hamlets (out of 895 in the middle) with within-hamlet variation. In column 2, the dependent variable is an indicator for whether the pixel has more than 3 floors, adding strata fixed effects for the photographic sample and a *NoBuilding* indicator. The dependent variable for column 3 is log of building height, restricted for a sample of 17,233 pixels with buildings. Standard errors are clustered by locality.

observations and hamlet fixed effects. We find qualitatively larger effects in areas in the top quintile of the predicted land index, followed by the next quintile, and so on. We also considered K-means clustering to group sub-blocks using the predicted land index and latitude and longitude.

5.3 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 low-quality kampungs 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 $\beta_I < \beta_{II} < \beta_{III}$.

Table 4: Heterogeneous effects by KIP waves

Dependent variable:	**Log land values**			**1(Height>3)**		
Sample:	Full Sample	Full Sample	Historical Kampung	Full Sample	Full Sample	Historical Kampung
	(1)	(2)	(3)	(4)	(5)	(6)
KIP I (1969-1974)	-0.44***	-0.03	-0.11	-0.13***	-0.07**	-0.10***
	(0.08)	(0.07)	(0.11)	(0.03)	(0.03)	(0.03)
KIP II (1974-1979)	-0.31***	-0.14**	-0.09	-0.09***	-0.05**	-0.10***
	(0.07)	(0.06)	(0.07)	(0.01)	(0.02)	(0.02)
KIP III (1979-1984)	-0.18**	-0.09**	-0.10	-0.07***	-0.04*	-0.10***
	(0.08)	(0.04)	(0.08)	(0.02)	(0.02)	(0.03)
N	19848	19848	3144	19515	19515	5277
R-Squared	0.57	0.85	0.74	0.16	0.36	0.29
p-val ($H_0 : \lvert\beta_I\rvert \leq \lvert\beta_{II}\rvert$)	0.06	0.90	0.39	0.12	0.33	0.45
p-val ($H_0 : \lvert\beta_{II}\rvert \leq \lvert\beta_{III}\rvert$)	0.10	0.26	0.54	0.13	0.35	0.48
Control Group Mean	15.84	15.84	15.89	0.18	0.18	0.24
Infrastructure	Y	Y	Y	Y	Y	Y
Topography	Y	Y	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y	Y	Y
Distance to CBD bins	N	Y	Y	N	Y	Y
KIP investments	N	Y	Y	N	Y	Y
Geography FE	District	Hamlet	Locality	District	Hamlet	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 adds hamlet fixed effects and controls for KIP investments (see Table 7) and dummies for distance bins from the CBD. Column 3 restricts to the historical kampung sample with 3,144 sub-blocks and includes 196 locality fixed effects. Columns 4 through 6 present the analogous analysis for heights. Column 4 includes the full photographic survey sample corresponding to 19,515 pixels. Standard errors are clustered by locality.

Critically, we find a monotonic pattern consistent with selection bias, but it disappears once we include our granular fixed effects. In Table 4, column 1 shows a monotonic pattern using the full sample of assessed land values, with estimates for the three waves being -0.44 (wave I), -0.31 (wave II), and -0.18 (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 controls. Reassuringly, the differences in column 1 are greatly attenuated once we include hamlet fixed effects (column 2) and in the historical kampung specification with locality fixed effects (column 3). We do not have statistical power for this test with the BDD sample (there are not enough boundaries to separately identify an effect for each wave). In columns 4 through 6, we arrive at similar conclusions for building heights: there is a slight monotonic pattern but this weakens in the full sample and historical kampung specifications.

Other differences across waves One concern with our test is that the three waves may differ in other manners and not just by the selection rule. While it is difficult to separately identify negative selection across waves using a single cross-section of data, it is reassuring that our conclusions are robust to accounting for differences in program design across waves. Earlier KIP waves were implemented in older and more central parts of the city (see Figure A7). We address this by controlling for distance from the CBD, in addition to our granular fixed effects. Moreover, the investments provided by each of the three waves were not identical: for example, the first wave focused on sanitation and paving footpaths. We account for this by controlling for the intensity of KIP-provided investments.[23] Reassuringly, including these additional controls capturing program differences does not change the estimates of our coefficients of interest, once we include our fixed effects.

In addition, we note that there should be little heterogeneity associated with the timing of the physical upgrades for different waves as they have all likely depreciated by 2015, as discussed in Section 6.3. Finally, another concern is that the earlier waves had more time to be redeveloped. We note that development activity would only take off in the 2000's (see Section 7.7), well after KIP ended, suggesting that the gap between the first and last waves did not lead to a meaningful difference in redevelopment potential.

Overall, while we observe differences indicative of program selection bias, it is reassuring that these differences are greatly attenuated in the historical kampung and full sample specifications. These results are in line with descriptions of the convergence of KIP and non-KIP kampungs documented in World Bank (1995). Section 8.2 below further probes whether historical differences between KIP and non-KIP can explain our results, reaching similar conclusions.

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

We now examine potential factors associated with lower land values and building heights in KIP. In line with the policy makers' perception that upgrading makes slums more persistent, we consistently find that KIP areas are more likely to be informal across all proxies of informality. We find less support for other channels, such as direct effects of KIP upgrades and current public amenities.

[23] From our 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).

6.1 Informality

Figure A5 shows that KIP areas are more likely to be informal today, using the full photos sample and our rank-based informality index for treated and control pixels. 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.

Table 5 considers two measures of informality. Columns 1 through 3 indicate that KIP neighborhoods are more likely to be informal using the photo rankings. The magnitudes range from 0.27 to 0.32, relative to a control group mean of 1. Columns 4 to 6 show the share of a pixel with unregistered titles is higher by 2 to 3 p.p. in the full and historical samples. The effects are insignificant for the BDD specification.[24]

Table 5: Effect of KIP on informality

Dependent variable:	**Rank-based index**			**Unregistered parcels (shares)**		
Sample:	Full Sample	Historical Kampung	BDD 200m	Full Sample	Historical Kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	0.27***	0.32***	0.27***	0.02**	0.03***	-0.01
	(0.03)	(0.06)	(0.08)	(0.01)	(0.01)	(0.03)
N	19515	5277	4128	19515	5277	4128
R-Squared	0.54	0.25	0.47	0.47	0.35	0.57
Control Group Mean	1.11	0.96	1.12	0.13	0.18	0.15
Infrastructure	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	N	Y	N	N	Y
Geography FE	Hamlet	Locality	KIP boundary	Hamlet	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 4, 5, and 6. The dependent variables include the rank-based informality index (columns 1, 2, and 3; higher values correspond to more informal) and area share of a pixel with unregistered titles (columns 4, 5, and 6). Standard errors are clustered by locality (full sample and historical specifications), and by KIP boundary (BDD specification).

6.2 Density

Next, we consider parcel and household density. All else equal, both are proximate factors that could contribute towards delaying formalization. Relocation costs are likely higher in dense neighborhoods. Additionally, land assembly costs increase with parcel density, as more claimants exac-

[24]We find similar results using our alternative attributes-based index, which is less susceptible to subjectivity. For the subset of photos for which we coded individual attributes (7,101 pixels), we find that KIP areas have worse vehicular access, lower observable neighborhood quality, and less permanent structures, but we lack statistical power.

erbate ownership disputes and holdout problems. Columns 1 through 3 of Table 6 show that KIP areas have 9 to 13 more parcels per pixel, with an average of 13 to 19 parcels per pixel in non-KIP areas. Besides our standard controls, we also include the total log length of roads in the pixel, as the presence of road intersections may mechanically increase observed land fragmentation.

Table 6: Effect of KIP on parcel and household density

Dependent variable:	**Parcel density**			**Log household density**		
Sample:	Full Sample	Historical Kampung	BDD 200m	Full Sample	Historical Kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	10.13***	8.59***	12.61***	0.41***	0.31***	0.46***
	(0.55)	(1.06)	(1.04)	(0.02)	(0.04)	(0.05)
N	88832	11002	14951	69754	9809	14649
R-Squared	0.52	0.51	0.61	0.51	0.41	0.59
Control Group Mean	12.80	18.70	13.80	8.17	8.61	8.24
Infrastructure	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	N	Y	N	N	Y
Geography FE	Hamlet	Locality	KIP Boundary	Hamlet	Locality	KIP Boundary

* 0.10 ** 0.05 *** 0.01

Notes: This table reports the effects of KIP on the number of parcels in a pixel (columns 1 to 3) and log household density (columns 4 to 6). Columns 1 to 3 repeat the pixel-level specifications of Table 2, adding the log length of roads in a pixel as a control. Columns 4 to 6 report effects for household density in a pixel, logged. Standard errors are clustered by locality except for the boundary analysis where we cluster by KIP boundary.

In a similar vein, columns 4 through 6 show that household density in KIP is higher by 31 to 46 log points. Applying the 41 log points for the full sample to the corresponding control group mean, we find an effect of 14 more households per pixel, in line with the parcel density estimates.[25] 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 provide a suggestive test using historical population density in Section 8.2 (Table A8).

6.3 Amenities

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

[25] Assuming one to two households per parcel, 10 more parcels per pixel (from column 1) implies 10 to 20 more

Table 7: Heterogeneous effects by KIP components

Dependent variable:	Log land values	
Sample:	Full Sample	Historical Kampung
	(1)	(2)
KIP	-0.11***	-0.09*
	(0.04)	(0.05)
Length of Vehicular Roads (in km)	-0.02	-0.03
	(0.02)	(0.03)
Length of Pedestrian Roads (in km)	0.01	-0.01
	(0.02)	(0.02)
Number of Sanitation Facilities	0.003	0.01
	(0.01)	(0.01)
Number of Public Buildings	0.01	0.01
	(0.02)	(0.03)
KIP X Length of Vehicular Roads	0.004	-0.001
	(0.02)	(0.03)
KIP X Length of Pedestrian Roads	-0.01	-0.01
	(0.02)	(0.02)
KIP X Number of Sanitation Facilities	-0.004	0.002
	(0.01)	(0.01)
KIP X Number of Public Buildings	0.02	-0.02
	(0.02)	(0.03)
N	19848	3144
R-Squared	0.85	0.73
Control Group Mean	15.80	15.80
Infrastructure	Y	Y
Topography	Y	Y
Landmarks	Y	Y
Geography FE	Hamlet	Locality

* 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 full sample specification with hamlet fixed effects. Column 2 presents historical kampungs with locality 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.

Initial KIP investments. Table 7 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 sub-block, we quantify the intensity of KIP investments located within a 500 meter

households per pixel, inclusive of 14 more households.

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).

Columns 1 and 2 report the results for the full and historical samples, respectively. 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. We consider two types of current amenities. First, we observe public amenities in 2016 from OpenStreetMap. We measure distance of each pixel to the closest school, hospital, police station, and bus stop. Second, as a proxy for amenities associated with formalization, 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.

Table A3 shows that KIP areas today have similar access to public amenities (columns 1 through 4), but fewer formal amenities. Differences in access to the nearest school, hospital, police station, and bus stop are not large enough to 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 "caught up" (p. 6) as a result of broader economic growth in Jakarta. Columns 5 and 6 show that KIP areas have 1 p.p. lower retail density and 2 through 4 p.p. lower office density, in line with our findings of lower land values, lower heights, and more informality.

7 Model

So far, we have documented lower land values and heights in KIP neighborhoods. Mapping land values to welfare is complicated in our setting because the losses of displaced slum residents may not be readily captured. Will there be societal gains from removing KIP and, if so, where are the gains largest and how can we mitigate losses to the poor? In this Section, we develop and estimate a spatial equilibrium model to shed light on the welfare implications of KIP. The model includes key characteristics of developing country cities by featuring heterogeneous households and formal and informal housing markets (Tsivanidis, 2023, Gechter and Tsivanidis, 2023).

Below we outline the residents' and the developers' problem, and define the equilibrium conditions. We then discuss how we estimate key parameters in the model to match the reduced-form moments. The full derivation is provided in the Appendix. Our reduced-form estimates above identify the local, direct effects of KIP but do not account for spatial linkages and spillovers with the rest of the city that will be important in spatial equilibrium. The model allows us to consider policy counterfactuals that account for these forces and assess the aggregate and heterogeneous impacts of lifting KIP restrictions in the city as a whole and in different regions. We conclude with robustness and possible extensions of the model.

7.1 Residents

There is an open city, embedded in a broader economy, comprising a discrete set of locations $i \in \{1,...,N\}$. It is populated by a continuum of workers of type $g \in \{H,L\}$, representing high- and low-skilled. Conditional on moving to the city, residents choose where to live (i) and where to work (j), drawing two idiosyncratic preference shocks υ_i^g and ε_j^g, and how much housing to consume. The indirect utility of individual ω of type g living in i and working in j is:

$$U_{ij\omega}^g = (u_i^g)^{\rho^g} Y_{ij}^g (r_i^g)^{(\beta^g-1)} \varepsilon_{i\omega}^g \upsilon_{j\omega}^g. \tag{2}$$

Following Tsivanidis (2023), the indirect utility depends on amenities, rents, and housing consumption. We assume the housing market to be segmented into two types of housing, also indexed by g, each of which is consumed by group g residents only. Preferences are Cobb-Douglas over a numéraire consumption good and housing, reflected in the term $Y_{ij}^g (r_i^g)^{(\beta^g-1)}$, where r_i^g denotes housing rents per square meter of built-up space and (1-β^g) is the budget share spent on housing. Resident ω's income is Y_{ij}^g, which includes a workplace-specific wage w_j^g that is discounted by commuting costs d_{ij}. The two taste shocks are drawn independently and sequentially from a Fréchet distribution with shape parameter $\theta > 1$. This is robust to assuming simultaneous draws.

Locations are differentiated by amenities and rents. The term u_i^g is a bundle of local amenities, with ρ^g governing type g preference weight. It includes an exogenous component $\bar{u}_i^g$ and an endogenous one that depends on the share of type-H residents: $u_i^g = \bar{u}_i^g \cdot (Sh_i^H)^{\mu^g}$. Exogenous amenities $\bar{u}_i^L$ include basic public goods and tenure security, which are plausibly higher in KIP locations, whereas $\bar{u}_i^H$ may include public space and landscape amenities. Both types benefit from $(Sh_i^H)^{\mu^g}$, which captures positive spillovers (e.g. through agglomeration and job access) from having many H-type neighbors. In line with the literature (Diamond, 2016, Su, 2022), we assume that the low-skilled benefit less from these spillovers ($\mu^H > \mu^L > 0$).

The residents' problem is solved by backward induction. The share of group g residents choosing to live in i is:

$$p_i^g = \frac{\Phi_i^g}{\sum_i \Phi_i^g} \tag{3}$$

where $\Phi_i^g \equiv [(u_i^g)^{\rho^g}(\overline{Y}_i^g)(r_i^g)^{(\beta_g-1)}]^\theta$. $\overline{Y}_i^g$ denotes the expected income of location i residents given their optimal workplace choice. It is a function of residential commuter market access ($RCMA_i$) (Tsivanidis, 2023), a term summarizing access to jobs from location i. We focus on the choice of where to live and relegate details about workplace choices to the Appendix (Section B.1.1).

The expected utility of group g residents in the city (our welfare metric) is:

$$\overline{U}^g \propto \left(\sum_i \Phi_i^g\right)^{1/\theta}. \tag{4}$$

The total measure of residents of each type choosing to live in the city, $\overline{L}^g$, is pinned down by the expected utility in the city $\overline{U}^g$ vis-à-vis the outer economy.[26]

7.2 Developers

The supply side is similar to Gechter and Tsivanidis (2023) and Sturm et al. (2023). Each location i comprises a continuum of plots. In each plot, an atomistic landowner chooses (i) whether to develop the plot to provide formal ($g = H$) or informal ($g = L$) housing and (ii) how many floors to build, denoted by h_i^g.[27]

In the formal sector, heights are elastic with convex construction costs per unit land equal to $c^H(h_i^H) = k_i(h_i^H)^\nu$, with $\nu > 1$ and k_i denoting a local cost shifter (Sturm et al., 2023).[28] At baseline, we assume that the informal technology only allows buildings of one floor ($h_i^L = 1$) at a fixed cost $\bar{c}^L$ per unit land, but we relax this assumption in a robustness exercise.

Only a share ϕ^g of each plot is buildable, with $\phi^H < \phi^L$ reflecting greater horizontal coverage in slums (Henderson et al., 2020). Profits per unit land for each land use type are:

$$\pi^L = (r_i^L - \bar{c}^L) \cdot \phi^L \tag{5}$$

$$\pi^H = (r_i^H - c^H(h_i^H)) \cdot h_i^H \cdot \phi^H. \tag{6}$$

Formal profits are further subject to formalization costs τ_i, reflecting land market frictions.

[26] The following mobility condition holds: $\overline{L}^g = \overline{L}^g_{econ} \frac{\overline{U}^g}{\overline{U}^g + \tilde{U}^g}$ where the constant $\overline{L}^g_{econ}$ denotes the total measure of residents in the economy and $\tilde{U}^g$ is the (fixed) expected utility in the outer economy.

[27] We assume all land is residential, abstracting from the trade-off between commercial and residential land use, and adjust the areas accordingly when taking the model to the data.

[28] This functional form can be derived from a Cobb-Douglas production function in land and capital, which is supported empirically in Combes et al. (2011).

These include, for example, land assembly costs associated with fragmentation which could plausibly be higher in KIP areas. Additionally, each plot is subject to idiosyncratic profits shocks (ζ_H, ζ_L) for each type of land use, jointly drawn from a Fréchet distribution with shape parameter $\gamma > 1$. Each plot owner thus chooses land use type g to maximize $\{(1-\tau_i)\pi^H\zeta^H, \pi^L\zeta^L\}$.

The resulting share of plots in location i allocated to formal land use is:

$$\lambda_i^H = \frac{((1-\tau_i)\pi_i^H)^\gamma}{((1-\tau_i)\pi_i^H)^\gamma + (\pi_i^L)^\gamma} \tag{7}$$

with the corresponding informal share being $\lambda_i^L = 1 - \lambda_i^H$.

The total supply of housing floorspace of type g in location i is

$$H_i^g = \lambda_i^g \cdot T_i^g \cdot h_i^g \cdot \phi^g \tag{8}$$

where T_i^g represents a local zoning tax (Sturm et al., 2023).

We assume that all land is owned by residents, consistent with the majority (75%) of kampung dwellers reporting to be owners (see Section 2.2). As in Tsivanidis (2023), we assume that land profits are redistributed equally to all residents within each group through lump-sum payment $\bar{r}^g$.[29] This ensures that all the gains (producer and consumer surplus) are accounted for in our welfare metric without having to separately account for absentee landlords.

7.3 General Equilibrium

An equilibrium is defined as a vector of endogenous objects $\left(L_i^g, \lambda_i^g, h_i^g, r_i^g\right)$ such that the following conditions hold for all i:

(i) **Location Choice:** The number of group g residents in each location, L_i^g, is consistent with neighborhood choice (3):

$$L_i^g = p_i^g \overline{L}^g. \tag{9}$$

(ii) **Land Use:** The share of land in each location allocated to formal land use is consistent with developer optimization as per (7).

(iii) **Profit Maximization:** Building heights h_i^H are consistent with profit maximization:

$$r_i^H = k_i \nu h_i^{H(\nu-1)}. \tag{10}$$

[29] Specifically we have: $\bar{r}^g = \frac{\sum_i (1-\tau_i^g)\pi_i^g \lambda_i^g T_i^g}{\bar{L}^g}$ with $\tau_i^H = \tau_i$ and $\tau_i^L = 0$. Total income is thus $Y_{ij}^g = (w_j^g/d_{ij}) + \bar{r}^g$.

(iv) **Floorspace Market Clearing:** Aggregate floorspace demand equates floorspace supply in each location:

$$\frac{L_i^g(1-\beta^g)\overline{Y}_i^g}{r_i^g} = \lambda_i^g \cdot T_i^g \cdot h_i^g \cdot \phi^g. \tag{11}$$

7.4 Calibration

To highlight the gains from lifting KIP at different distances from the CBD, similar to Henderson et al. (2020), we categorize Jakarta into 5 km-wide distance bands (indexed by I). In each of the three innermost regions we have a non-KIP and a KIP counterpart and we use the outermost, non-KIP-only region for normalization, resulting in 7 locations in total. We address robustness to the choice of spatial units in Section 7.6 below. For non-KIP locations, we assign population, rents, heights, and land shares from the data. The KIP counterparts are constructed to match the reduced-form KIP effects for the center/middle/peripheral regions (Table 3). This approach integrates the identifying assumption of the reduced-form that the estimated wedges between KIP and non-KIP are due to the policy and not to other differences. Through the lens of the model, wedges in land values and building heights between KIP and non-KIP locations arise from differences in location fundamentals (τ_i, $\overline{u_i}^g$).

Below we outline the main data preparation steps, our approach to construct KIP counterparts, and the calibration of the key model parameters. Further details are provided in the Appendix.

Data preparation. To take the model to the data, we need to observe formal *and* informal rents (r_i^g), population, (L_i^g), building heights (h_i^g), and land shares (λ_i^g) in non-KIP locations. We classify pixels as informal if the parcel density is in the top quartile (over 24 parcels per pixel) and define the informal land share λ_i^L accordingly. Similarly, we classify land values and heights observations to H or L based on the parcel count in the corresponding pixel. We then calculate rents (r_i^g) using land values and heights to infer the value of the structure (see Section B.2.1). In order to disaggregate population counts by H and L, we predict the likelihood of living in an informal area using a battery of household characteristics from the Census, such as age, gender, education, marital status, migrant status, and being economically active. We define endogenous amenities Sh_I^H as the share of H-types in each region, allowing for amenity spillovers to be common across the KIP and non-KIP portion.

Matching moments. Next, we use the model to generate wedges in land values and heights and match those to the empirical ones. We interpret the wedges estimated in our reduced-form KIP/non-KIP comparisons as direct KIP effects on the own-region, without allowing for indirect effects such as sorting and spillovers involving the broader economy. From these model-predicted wedges and non-KIP data, we construct model-implied counterfactual KIP counterparts. For the sake of illustration, consider region $I = Center$. We take $\left(L_i^g, \lambda_i^g, h_i^g, r_i^g\right)$ for $i = (Center, NonKIP)$ from the data. For the KIP counterpart, we search for values of $\left(L_j^g, \lambda_j^g, h_j^g, r_j^g\right)$ for $j = (Center, KIP)$ that satisfy equations (7), (9), (10), (11) in the Center, taking the endogenous variables in all other locations as given, and that generate the reduced-form wedges in land values and heights estimated in Table 3 for the Center.

Model parameters. With actual and model-generated data in hand, we invert the model to retrieve (τ_i, $\overline{u_i}^g$). Formalization costs are pinned down by relative profits and land shares, rearranging equation (7). Amenities are identified from the location choice condition, leveraging observed population counts and rents. The Appendix discusses the calibration of the other relevant parameters. In particular, we calibrate $\overline{w_i}$ and commuter market access using granular employment data[30] and we estimate γ (the slum conversion elasticity) using the estimated cross-elasticity of informal land shares to formal rents. The remaining parameters are set to values taken from the literature or calibrated to match Indonesian/Jakarta moments, as summarized in Table 8.

Table 8: List of parameters, estimation methods, and sources

Parameter	Description	Value	Source
θ	Taste shock dispersion	3	Tsivanidis (2023)
$\frac{1}{(\upsilon-1)}$	Floorspace supply elasticity	1.45	Sturm et al. (2023)
μ^H	Amenity spillovers	0.88	Gechter and Tsivanidis (2023)
μ^L/μ^H		0.30	Diamond (2016)
β^H	Housing budget shares	0.17	SUSENAS household survey
β^L		0.13	(Badan Pusat Statistik (2008))
γ	Profit shock dispersion	1.18	Estimated from cross-elasticities of land shares to rents
u_i^H, u_i^L	Amenities		Calibrated from ratios of rents and household counts
τ_i	Formalization costs		Calibrated from ratios of land use shares

7.5 Counterfactuals

We now conduct counterfactual exercises to shed light on (i) what are the general equilibrium effects of lifting KIP today (ii) where the welfare gains are the largest and (iii) how to minimize losses for the L types.

[30] While our locations of residence are defined as above, we allow for spatial linkages via labor markets to occur among more granular spatial units (localities).

7.5.1 Effects of lifting KIP everywhere

In Table 9, Panel A, we consider a counterfactual where we lift KIP everywhere in the city. This amounts to setting $(\tau_i, \overline{u_i}^g)$ in each KIP region to match the values in the corresponding non-KIP region. We report percentage changes in $\overline{U}^g$ by groups in columns 1 and 2 and a weighted average of the two in column 3.

Overall, H types gains 5% and L types lose 2.1%, with the city as a whole experiencing welfare gains of 3.1% and a 2.3% population increase. Qualitatively, our findings are similar to those in Gechter and Tsivanidis (2023), who show that formal workers benefit from redevelopment whereas displaced informal residents are hurt.[31]

Our finding of city-wide gains associated with formalization also echo those in Henderson et al. (2020) for Nairobi. They find that if the Kibera slum were formalized and the slumlords fully compensated, each evicted slum household would be able to receive USD 18,000 or 26 times their annual rent. Performing a similar calculation for Jakarta, the total H-type gains from formalizing the center are equivalent to USD 29,300 per slum household (18 times the annual rent).

Table 9: Effects of lifting KIP

	H	L	All
Panel A: City-wide			
Welfare %	5.0%	-2.1%	3.1%
Population %	5.3%	-5.4%	2.3%
Panel B: By Region			
Welfare %			
Center	4.1%	-2.3%	2.4%
Middle	0.6%	-0.3%	0.4%
Periphery	0.2%	0.1%	0.2%

Next, we assess the role of direct versus general equilibrium effects in explaining the welfare result. First, we consider direct effects within region, without allowing for any linkages across regions. As KIP is lifted, the formalization cost is reduced, leading to an increase in the formal land share and lower H rents, which benefits H types. This also leads to a compression in the informal land shares and a consequent increase in informal rents, hurting L types. Additionally, L types are displaced away from KIP regions to lower-amenity locations. Furthermore, lifting KIP entails reducing the L-type exogenous amenities and enhancing H-type amenities, which exacerbates the

[31] Specifically, they find that the high-skilled gain 13%, not-evicted low-skilled gain 10%, and evicted low-skilled lose 23%. Their welfare metrics is not directly comparable. Additionally, they consider a policy change whereby formal high-rises are built in previously empty areas, whereas in our counterfactual we consider a less drastic increase in the rate of formalization induced by lifting KIP.

effects above. We find that the direct welfare impacts of lifting KIP are 4.5% for the H types and -3.1% for the L types, qualitatively and quantitatively close to the general equilibrium ones.

In general equilibrium, three additional forces come into play: residents resort across the city (from residence and workplace choice) and prices in other regions respond as governed by the elasticity of housing supply; there will be in- and out-migration, with more H types moving into the city and L types leaving; and endogenous amenity spillovers will manifest, resulting in additional resorting and price effects. Put together, the direct effects are driving the overall welfare impacts. In Section 7.6 below, we probe the robustness of this conclusion to using more granular spatial units.

7.5.2 Where to formalize

In Panel B of Table 9 we show that 77% of the gains stem from lifting KIP in the center. We consider three distinct counterfactuals whereby we lift KIP only in one region at a time. The center (within 5 km from the CBD) is where the reduced-form wedges in land values and heights are the largest (see Table 3). The gains for the H-types are the largest (4.1%) but so are the losses for the L-types (-2.3%). On net, the city-wide effects of 2.4% are 77% of the effects from lifting KIP in the entire city (3.1%). The key source of misallocation associated with KIP today is that the program is prevalent precisely in this part of the city (44% of the program area is in the center, relative to 43% in the middle and 13% in the periphery).

To corroborate our interpretation, we perform a placebo exercise in which we assume that the reduced-form wedges in land values and heights are the same across the three regions, as opposed to monotonic. We set each to be equal to the area-weighted average of the three heterogeneous effects coefficients. We re-estimate the model and find that the counterfactual gains from lifting KIP everywhere are only 0.5% overall. We also confirm that our baseline result of largest gains in the center is not mechanically generated by differences in the area sizes of the different regions.[32]

Elsewhere, we find small city-wide effects (0.4% and 0.2% respectively from lifting KIP in the middle or the periphery). This is notable since around half of the program area is in the middle and periphery and our calculations suggest minimal inefficiencies associated with slum upgrading in these areas.

[32] We do so by performing another placebo exercise in which we set the land area in each region to be the same. We continue to find that the majority of the gains stem from lifting KIP in the center.

7.5.3 How to formalize

Finally, we turn to the question of how to formalize in a way that balances equity and efficiency. In Table 10 we consider two examples of policies that can be bundled with formalization to alleviate the losses of the L types while preserving sizable gains for the H types: one is to promote taller formal buildings, thus reducing the extent of displacement of the L types; the other is to redistribute land rents from H to L types.

Consider a scenario in which a quarter of KIP's land area in the center can be formalized (12 squared km). Lifting KIP restrictions would entail a loss for the L types (-0.06%). If this is bundled with a zoning policy allowing for taller formal buildings (which we implement in the model by boosting ν by 25% or 35%), the L type losses are reversed (0.004% and 0.03%), while the gains of the H types are also enhanced. Taller buildings allow total formal floorspace to increase and H share spillovers to be realized without displacing as many informal households.

An alternative way to alleviate the losses is to redistribute part of the land rents across groups. If the H-types give up 5% of their lump sum $\bar{r}^H$ and this is transferred to the L types, both groups gain. This abstracts from the institutional challenges and political economy considerations that make implementing these transfers difficult in practice.

Table 10: Balancing equity and efficiency

Welfare %	H	L	All
Lift KIP	1.23%	-0.06%	0.88%
Lift KIP & zoning height boost ($\Delta\nu$ = 25%)	1.39%	0.004%	1.01%
Lift KIP & zoning height boost ($\Delta\nu$ = 35%)	1.45%	0.03%	1.06%
Lift KIP & redistribute 5% H rents	0.98%	0.33%	0.80%
Lift KIP & redistribute 10% H rents	0.72%	0.73%	0.72 %

7.6 Robustness

Key model parameters We perform several sensitivity and robustness exercises. In Table B.1 we present the welfare gains from lifting KIP everywhere under different assumptions concerning open versus closed city and endogenous amenity spillovers.

Assuming a closed city the results are qualitatively similar to baseline, but the gains are more muted as we do not allow H types to move in. Endogenous spillovers from H types appear to be important, in line with the findings of the literature (e.g. Diamond (2016)). Assuming no spillovers preserves the qualitative patterns but reduces the magnitudes of the gains for both types. This suggests that the strength of the spillovers from formal areas, in the form of non-excludable public goods or access to employment opportunities, is important to determine the effects of formalization on the poor. Naturally, the relative strength of the amenity spillover parameter for L types drives the magnitude of the L type effects, with L types losing less if they benefit more from being close to H types.

In the Appendix (Section B.2.2) we also discuss robustness to the γ parameter, governing the sensitivity of formal and informal land shares to rents. Finally, we verified that our welfare conclusions are not driven purely by the wedges in land values, which could be measured with error. If we repeat our estimation assuming that the wedges in land values are flat across the three regions, whilst retaining the monotonic wedges in heights from center to periphery, we obtain a similar result that the majority of the gains stem from lifting KIP in the center.

Elastic informal supply A concern with our findings is that the price response of the informal sector may be artificially large because of our assumption of fixed heights. In practice, in the informal sector quantity can respond (Henderson et al., 2020). We probe this by considering elastic informal supply, with a production function similar to that of the formal sector, but with a lower elasticity of $\frac{1}{(\nu_L - 1)} = 1.3$, reflecting the estimates for the formal and informal sector in Henderson et al. (2020). Reassuringly, our estimated gains are similar to our baseline (3.3% city-wide gains from lifting KIP everywhere).

Finer spatial units Our conclusion that the majority of the gains stem from the center is robust to considering sub-districts as our spatial units i. We include 21 that (i) have both a KIP and a non-KIP portion and (ii) have both formal and informal observations for land values and heights in each portion. We lose half of Jakarta's sub-districts due to the sparseness of the data.

Subject to these caveats, our key patterns of larger gains in the center are preserved. Lifting KIP from all sub-districts, the weighted average gain is 2.6% and 95% of these gains are realized from formalizing sub-districts in the center. We then consider the effects of formalizing one sub-district at a time. Ranking sub-districts by the magnitude of the city-wide gains, all the sub-districts in the top quartile are in the center and all the districts in the periphery fall in the bottom two quartiles. We also continue to find that the majority of the gains are driven by direct effects. The partial equilibrium gains from formalizing all sub-districts is 2.8%.

7.7 Discussion

Put together, our welfare conclusions are suggestive that spatial misallocation is largely associated with KIP areas that are central. Indeed, a sizable share of the KIP program area is outside the center and we find limited gains from removing KIP in those areas.

An important caveat is that our model is static and our efficiency claims may not always carry through to a dynamic setting. To the extent that the relative gains from formalizing the center will continue to be large, the presence of KIP in the center going forward will be inefficient in a dynamic sense as well. However, there could be a reversal if the center of Jakarta loses its primacy as a result of natural disasters (e.g. flooding), urban blight leading to flight from the center, or the city becoming polycentric. The relative returns to redeveloping different areas may also change as a result of infrastructural investments (e.g. mass rapid transit improving access in the middle and periphery), zoning, or other policy changes (e.g. moving government offices away from Jakarta and to the new capital city). This implies that the dynamically optimal allocation of slum upgrading across the city depends on the social planner's stance on the future evolution of fundamentals across neighborhoods and its ability to direct it.

Additionally, we note that our welfare exercise speaks to potential efficiency gains from lifting KIP today but cannot speak to the cumulative welfare effects of the KIP program overall. In order to assess whether it was *ex ante* dynamically inefficient, we would need to calculate the expected present discounted value of the flow of short-run KIP benefits on residents vis à vis the long-run gains from formalizing. Without historical data, we cannot estimate the benefits of KIP on past beneficiaries that have been displaced by formalization.

If the direct KIP benefits from physical upgrades and enhanced tenure security were particularly large in the center and accrued over a long time, it is possible that implementing KIP and delaying formalization in the center was actually optimal. For example, there could be differential intergenerational mobility for KIP residents who stay in central areas versus non-KIP residents displaced to the periphery (Rojas-Ampuero and Carrera, 2023).

8 Threats to identification and robustness

This Section discusses threats to the identification of our reduced-form estimates. We discuss potential confounding due to spatial spillovers, persistence, and endogenous sorting and describe additional robustness checks.

8.1 Spillovers and BDD robustness

Below, we empirically assess the role of spillovers. Overall, there is suggestive evidence of spillovers but the patterns are not significant enough to change our conclusions.

Our setting is likely to feature spatial spillovers between treated and control areas. For example, our local KIP estimates may be biased by spillovers *from KIP to non-KIP* areas. These could take the form of negative externalities from slums (e.g. from unsanitary living conditions or crime), leading to underestimating the KIP effects, or positive externalities from the KIP upgrades, leading to overestimates. The latter seem unlikely given our findings from Section 6.3 above, where we show no differential KIP effects by access to the initial KIP upgrades (Table 7). Additionally, there could be spillovers *from non-KIP to KIP*, in the form of positive externalities from gentrified areas (e.g. from access to jobs or public goods), also leading to underestimating the KIP effect.

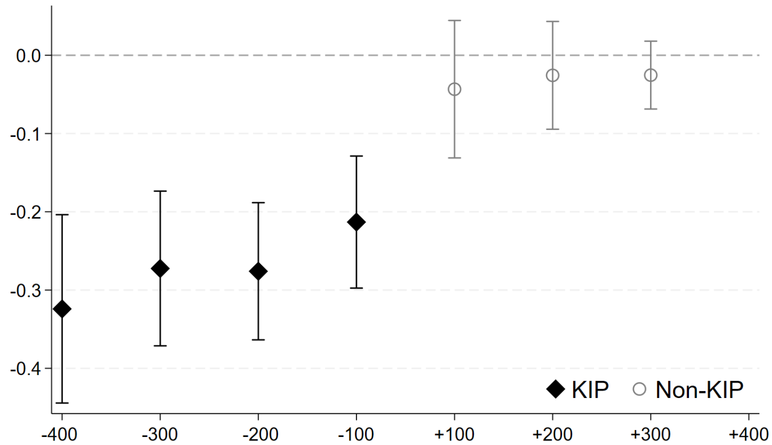
Spatial decay on both sides of KIP boundaries Figure 3 investigates the extent of spillovers by analyzing patterns of spatial decay, under the premise that localized exposure effects should decline with distance (Turner et al., 2014, Anagol et al., 2021). We focus on distance bands of up to 500 meters.[33] We employ a similar specification as our BDD analysis, replacing distance to the KIP boundary with dummies for different 100 meter-wide distance bins. The spatial decay patterns for land values, heights, and parcel density remain relatively stable, albeit with wide confidence intervals. We do not detect a significant enough pattern that can materially change our conclusions.

Spatial decay from non-KIP slums We further probe the concern that our estimates may be biased by negative externalities from slums by considering spatial decay away from non-KIP slums (which cannot be confounded by the program) that have high population density (thus more likely to generate congestion externalities). Figure A8 shows limited evidence of spatial decay on land values and heights, conditional on our controls. There is a slight pattern of higher parcel density near the boundary, which is suggestive of negative spillovers, but the confidence intervals are large. Overall, we find limited scope for negative spillovers from slums. This is consistent with the prominence of gated communities in formal neighborhoods and the moderate crime levels in in Jakarta. This finding also addresses the concern that lower land values in KIP may be driven by congestion and higher density alone, regardless of delayed formalization.

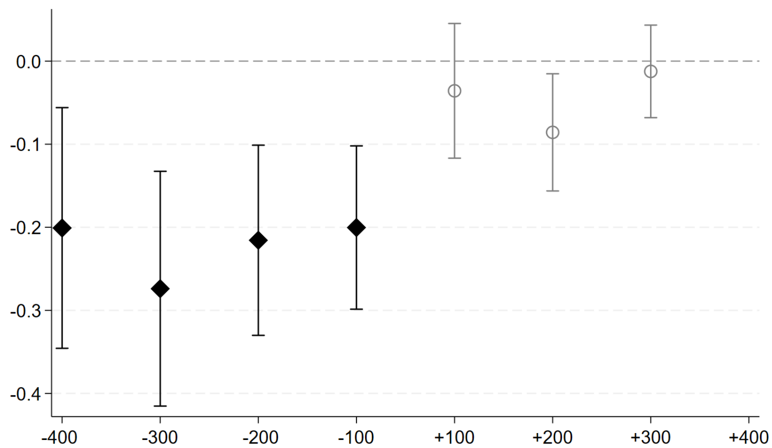
BDD robustness In line with the spatial patterns above, Table A4 shows that our BDD estimates are similar if we consider alternative buffer distances (the optimal bandwidth as per Calonico et al. (2014) and 500 meters). We also consider alternative cutoffs to exclude contaminated controls in Table A5. Table A6 shows that our BDD estimates are also robust to excluding boundaries that overlap with historical and contemporaneous waterways and roadways.

[33] Our automated procedure which assigns observations to the closest boundary results in a majority of treated observations being within 500 meters of KIP boundaries. We also consider spatial decay all the way to 1000 meters and our conclusions remain the same. Empirical estimates from the urban literature suggest spillovers decay relatively sharply within 500 meters and tend to dampen out beyond 1000 meters (Diamond and McQuade, 2019, Rossi-Hansberg et al., 2010, Autor et al., 2014, Campbell et al., 2011).

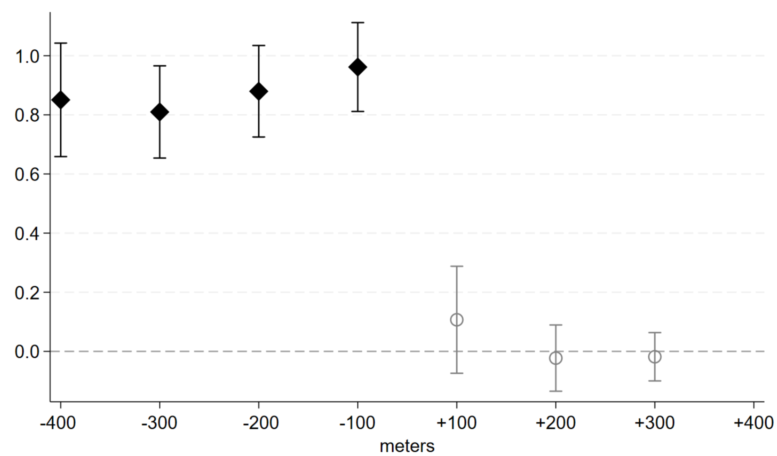
Figure 3: Spatial decay: distance from KIP boundaries



(a) Log land values



(b) Log building heights



(c) Log parcel density

Notes: We employ a similar specification as our BDD analysis in Table 2, replacing distance to the KIP boundary with dummies for different 100m-wide distance bins, pooling the two outermost bins for 400m and 500m.

8.2 Persistence

Next, we consider the role of persistence in pre-KIP differences. Formally, assume that unobserved quality in pixel i in neighborhood j evolves according to the following process: $\xi_{ijt} = \rho\xi_{ij,t-1} + u_{jt} + \varepsilon_{ijt}$ where $\rho < 1$, u_{jt} is a contemporaneous neighborhood component, and ε_{ijt} is a mean 0 idiosyncratic shock. To trace back to pre-KIP differences, let the beginning of KIP be $t = 0$ and modern Jakarta be 40 years later. The potential selection bias comparig KIP (K) and non-KIP (NK), $E(\xi_{ijt}|K_{ij}, \mathbf{X}_{ij}, \delta_j)$ - $E(\xi_{ijt}|NK_{ij}, \mathbf{X}_{ij}, \delta_j)$, can be expressed in two components stemming from pre-KIP factors and contemporaneous factors. Our identifying assumption is that both components are small conditional on granular fixed effects (δ_j) and controls ($\mathbf{X}_{ij}$):

$$\underbrace{\rho^{40}\left[E\left(\xi_{ij0}|K_{ij}, \mathbf{X}_{ij}, \delta_j\right) - E\left(\xi_{ij0}|NK_{ij}, \mathbf{X}_{ij}, \delta_j\right)\right]}_{\text{Muted impact from pre-KIP differences}} - \underbrace{\left[E(u_{jt}|K_{ij}, \mathbf{X}_{ij}, \delta_j) - E(u_{jt}|NK_{ij}, \mathbf{X}_{ij}, \delta_j)\right]}_{\text{Common shocks are differenced out}}$$

Below we examine several dimensions of historical neighborhood quality: whether a neighborhood was a kampung initially, which could confound our full sample and BDD estimates, and initial population density, which was part of the program selection rule. In line with the literature on persistence in cities (e.g. Ambrus et al. (2020), Bleakley and Lin (2012)), we find evidence that historical conditions matter, but are unlikely to explain our results.

Persistence of slums Table 11 presents a falsification test to address potential confounding of our BDD estimates due to the generic persistence of slums. We implement a specification similar to our BDD one, but we consider historical slum boundaries in non-KIP areas as placebo borders. Specifically, we include non-KIP observations that are within 200 and 500 meters of a historical kampung boundary. This yields 45 and 41 boundary segments respectively.

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 within a 200 meter and a 500 meter distance band. The limited evidence of a historical slum effect at the boundary is in line with our finding of limited decay in land values away from dense slums presented in Section 8.1 (Figure A8). We caveat that in the exercises above we are considering non-KIP slums, that were higher-quality initially than KIP slums. We did not collect photos for heights around the placebo boundaries.

Persistence of historical density Table A7 explores the role of pre-KIP population density, one of the criteria in the scoring rule. We observe 1960 population at the locality level from the Census and define a dummy for localities in the top two densest quintiles.

Consistent with crowding and persistence, land values are 13 log points lower in historically

Table 11: Effect of placebo boundaries

Dependent variable:	**Log land values**	
Sample:	BDD 200m	BDD 500m
	(1)	(2)
Kampung	-0.03	0.09
	(0.10)	(0.07)
N	1793	2631
R-Squared	0.50	0.50
Control Group Mean	15.28	15.32
Infrastructure	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 kampung 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.

denser places (column 2). The KIP effect remains stable around -34 log points with or without controlling for historical density, suggesting the potential bias from historical density is muted. Since historical density is defined at the locality level, we can only include fixed effects at the sub-district level (one level larger than localities). In column 3, we show we can recover a 9 log point effect using our baseline specification (with controls and hamlet fixed effects) in this Census-matched sample. [34] This is slightly different from the 11 log point using the full sample in Table 2 because we lost 4307 observations which cannot be matched with historical density. For heights (columns 3 to 6), the coefficient for KIP is similar with or without the dummy for pre-KIP density and column 6 recovers a similar 7 p.p. effect as we do above. The direct effect of pre-KIP density on heights is positive (column 2) most likely because those dense places are central and tend to have tall buildings.

[34] We also explore the extent to which selection of unobservables can play a role in this specification. Following Oster (2019), we calculate how large the bias from unobservables has to be to explain away the results, finding a ratio of 1.3, above the heuristic of 1. To do this, we compare the uncontrolled and controlled KIP estimates (-0.34 and -0.09, respectively) and we also compare the R-squareds (0.57 and 0.83, respectively). Using the formula $\frac{\beta_C}{(\beta_U-\beta_C)} * \frac{R_C-R_U}{R_{Max}-R_C}$, where U denotes uncontrolled and C denotes controlled, we calculate the ratio as $\frac{-0.09}{(-0.34+0.09)} * \frac{0.83-0.57}{0.9-0.83}$. Intuitively, this ratio will be large if the KIP effect is stable (first term), the R-squared improves a lot with controls (numerator of second term), or there is less remaining variation to explain (denominator of the ratio in the second term). We assume a maximum R-square of 0.9 (it is unlikely that assessed land values will have a maximum R-squared of 1, given measurement error (Oster (2019); Alesina et al. (2016)). The corresponding ratio for heights is 2.5.

Crowding over time Table A8 investigates whether KIP caused crowding by considering the KIP effect on decadal population density. We find a pattern suggestive of population density in KIP increasing over time, but the coefficients are not statistically significant.

Historical land institutions. A potential concern with our comparisons is that, historically, KIP and non-KIP areas may have been differentially titled. In our historical kampung specification, we only restrict the comparisons to (informal) kampungs so both KIP and non-KIP were likely comparable. The historical maps we use classify kampungs differently from "beboude kom" or "built-up" settlements that were titled under the Dutch cadastral system. As an additional check, in Table A9, we exclude all hamlets that have any "beboude kom" areas (a proxy for historical titling rates) and, reassuringly, our results are similar.

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 A10) and when restricting the sample to stayers (Table A11), which tends to go against the lower land values in KIP.

Table A12 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 A13 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 Other robustness checks

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 A14 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).

Standard errors robustness. We replicate the specifications in Table 2 using Conley (1999) standard errors with a radius of 200 meters, 500 meters, up through 1200 meters. The p-values for the KIP treatment effect are all below 2% and our conclusions under alternative standard errors specifications are unchanged.

9 Conclusion

We study one of the world's largest slum upgrading programs, the 1969 to 1984 Kampung Improvement Program, which upgraded slums for 5 million residents and covered 25% of land in Jakarta. On average, KIP areas have lower land values in 2015, shorter buildings and are more informal. The negative effects are largest within 5km of the CBD. We develop a spatial equilibrium model to quantitatively assess the role of slum upgrading in influencing spatial misallocation of land, finding that 77% of the welfare gains from removing KIP is associated with land close to the CBD. Elsewhere, removing KIP has minimal welfare implications.

Our findings deliver policy-relevant lessons for developing countries facing massive urbanization with severe shortages in housing. As cities are reshaped to accommodate urban growth (Harari, 2020, Lall et al., 2021), policy makers debate how to allocate land and where to upgrade and preserve slums, as well as how to alleviate losses to displaced residents.

There are several avenues for future research. Future work can be directed to comparing slum upgrading versus other shelter policies, such a public housing or sites and services. There are also open questions on how to design slum upgrading, including whether to bundle upgrades with titles and person-based as opposed to place-based approaches. More research is needed to understand how policy makers should trade-off the short-run benefits of upgrades and long-run opportunity costs from delayed formalization. Finally, it will be important to investigate the human capital implications and inter-generational spillovers involving slum residents who improve and transition into formal housing.

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Online Appendix

Appendix Tables

Table A1: Summary statistics

Variable name	N	Unit	Mean	SD
Panel A: Outcomes				
Log Assessed Land Values, Thousand Rupiahs per sqm	19848	sub-block	15.91	0.92
1(Height>3)	19515	pixel	0.17	0.37
Log Building Height, Number of Floors	17233	pixel	0.91	0.68
Rank-Based Informality Index	19515	pixel	3.33	14.32
Attribute-Based Informality Index	7101	pixel	0.05	0.44
Unregistered Parcels (shares)	19515	pixel	0.15	0.21
Parcel Density	88832	pixel	15.86	16.19
Retail Density	88832	pixel	0.02	0.10
Office Density	88832	pixel	0.04	0.16
Log Household Density	69754	pixel	8.33	0.81
Panel B: Controls				
Log Distance to Golden Triangle	19515	pixel	1.30	2.84
Log Distance to Historical Main Road, m	19515	pixel	8.23	1.10
Presence of Wells or Pipes within 1000m	19515	pixel	0.18	0.38
Log Average Distance to Railway Stations, m	19515	pixel	8.32	0.83
Log Average Distance to Tram Stations, m	19515	pixel	8.52	0.79
Elevation, m	19515	pixel	18.04	10.48
Slope, Degrees	19515	pixel	4.77	3.23
Log Average Distance to 1959 Waterways, m	19515	pixel	7.82	0.26
Flow Accumulation	19515	pixel	2.88	7.06
Log Distance to Coast, m	19515	pixel	8.93	0.87
Log Distance to Surface Water Occurrence, m	19515	pixel	7.46	0.93
Log Distance to Monument, m	19515	pixel	8.88	0.60
Log Distance to Tanjung Priok Harbor, m	19515	pixel	9.48	0.44
Log Distance to Old Batavia, m	19515	pixel	8.97	1.53
Log Distance to Concert Hall, m	19515	pixel	8.94	0.59
Log Distance to Hotel Des Indes, m	19515	pixel	8.93	0.63
Log Distance to Bioscoop Metropool, m	19515	pixel	8.86	0.62
Log Distance to Akademi Nasional, m	19515	pixel	9.21	0.59
Log Distance to Ragunan Zoo, m	19515	pixel	9.44	0.52

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 19,515 pixels in our photographic survey). Additionally, we manually reviewed the appearance of the photos for 7,101 pixels to construct the attribute-based informality index. We also report land use patterns (parcel, retail, and office density) for 88,832 pixels from an administrative dataset, and household density. Panel B reports summary statistics for controls measured at the pixel level.

Other building height outcomes

Table A2 repeats the building heights analysis for different height outcomes. In columns 1 through 3 we consider the number of floors for the tallest building in the pixel. The effect sizes range from -0.8 to -1.6 floors. In columns 4 through 6 we consider log number of floors, conditional on having at least one building in the pixel. We obtain effect sizes ranging from -9 to -19 log points. In the BDD sample the effects are insignificant but qualitatively similar to the historical kampung ones.

Table A2: Robustness checks for building heights

Dependent variable:	**Building Heights**			**Log height**		
Sample:	Full Sample	Historical Kampung	BDD 200m	Full Sample	Historical Kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.83***	-1.61***	-1.53	-0.09***	-0.19***	-0.18
	(0.31)	(0.37)	(1.28)	(0.03)	(0.04)	(0.13)
N	19515	5277	4128	17233	5061	3923
R-Squared	0.39	0.32	0.47	0.41	0.37	0.55
Control Group Mean	3.24	5.12	3.60	0.92	1.13	0.97
Infrastructure	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	N	Y	N	N	Y
Geography FE	Hamlet	Locality	KIP boundary	Hamlet	Locality	KIP boundary

* 0.10 ** 0.05 *** 0.01
Notes: This table reports specifications similar to those in Table 2 for the height dummy. Standard errors are clustered by locality, except for the BDD where we cluster by KIP boundary.

Current amenities

Table A3 investigates differences in access to current amenities. Columns 1 through 4 focus on public amenities. 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. There is a 7% effect for hospitals the historical sample (panel B) which translates to 70 meters; this is small relative to a mean of 1000 meters and the corresponding full sample coefficient is 3% (panel A). There is a 31% effect for bus stops in the historical sample (panel B) which is equivalent to 258 meters (moderate relative to a mean of 835), but its full sample counterpart is only 7% in the full sample. These differences 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.

Columns 5 and 6 show that KIP areas have fewer formal commercial developments, with 1 p.p. lower retail density and 2 p.p. (panel A) to 4 p.p. (panel B) 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 A3: 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: Full Sample						
KIP	-0.02	0.03**	0.01	0.07***	-0.01***	-0.02***
	(0.03)	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)
N	88832	88832	88832	88832	88832	88832
R-Squared	0.51	0.78	0.87	0.85	0.25	0.40
Control Group Mean	0.50	1.30	2.01	1.69	0.02	0.05
Panel B: Historical Kampung						
KIP	0.05	0.07*	0.005	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	0.72	0.56	0.16	0.26
Control Group Mean	0.42	1.10	1.67	0.94	0.03	0.06
Infrastructure	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 88,861 pixels in the full sample (Panel A) and 11,002 pixels in the historical kampung (Panel B). Standard errors are clustered by locality.

Robustness for boundary analysis

Table A4 considers different buffer distances. Odd colums consider 500 meters and even columns consider the optimal bandwidth as per Calonico et al. (2014)), which is 270 meters for log land values and 149 meters for the height indicator. We find similar effect sizes with KIP areas having land values that are lower by 17 to 18 log points and a likelihood of having tall buildings that is between 9 and 11 p.p. lower. The stability of the estimates across the buffer distances is in line with our limited evidence of spatial spillovers at the KIP boundary (Section 8.1).

Table A5 considers different distance cutoffs to define non-contaminated controls. At baseline, we exclude from the control group any non-KIP observation that is at a distance smaller than 200 meters from the second nearest KIP boundary segment. In this table, odd (even) columns exclude non-KIP observations that are within 100 meters (300 meters) from the second nearest KIP boundary respectively. Our results are robust to excluding observations within 100 meters but we are underpowered when we exclude too many non-KIP observations (300 meters).

Next, Table A6 shows that the land values estimates are similar when excluding boundary segments that overlap with railways (18 boundaries, column 1), waterways (61 boundaries, column 2), or both (73 boundaries, column 3). We consider contemporaneous railways and waterways as per OpenStreetMap as well as historical ones from the maps we utilize for our infrastructural controls. Our conclusions are similar for heights (columns 3 through 6).

Table A4: Boundary analysis, robustness to different bandwidths

Dependent variable:	**Log land values**		**1(Height>3)**	
	BDD 500m (1)	BDD Optimal (2)	BDD 500m (3)	BDD Optimal (4)
KIP	-0.17***	-0.18***	-0.09***	-0.11**
	(0.05)	(0.06)	(0.02)	(0.05)
N	7452	5314	7911	3297
R-Squared	0.82	0.82	0.41	0.56
Control Group Mean	15.90	15.80	0.19	0.22
Infrastructure	Y	Y	Y	Y
Topography	Y	Y	Y	Y
Landmarks	Y	Y	Y	Y
Distance to KIP boundary	Y	Y	Y	Y
Geography FE	KIP Boundary	KIP Boundary	KIP Boundary	KIP Boundary

* 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. Optimal bandwidths for log land values, 1(Height>3), and Log height are 270m, 149m, and 158m respectively.

Table A5: Boundary analysis, robustness to different distance cutoffs

Dependent variable:	Log land values			1(Height>3)		
Cutoff for distance to nearest KIP boundary:	200m	200m	200m	200m	200m	200m
Cutoff for distance to second nearest KIP boundary:	200m	100m	300m	200m	100m	300m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.18**	-0.14***	-0.06	-0.10***	-0.10***	-0.02
	(0.07)	(0.04)	(0.12)	(0.04)	(0.02)	(0.06)
N	4339	5659	3691	4128	6215	3155
R-Squared	0.84	0.84	0.84	0.53	0.47	0.54
Control Group Mean	15.70	15.90	15.50	0.21	0.23	0.17
Infrastructure	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.

Table A6: 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	-0.16**	-0.23***	-0.22**	-0.12***	-0.14***	-0.15***
	(0.07)	(0.09)	(0.09)	(0.04)	(0.05)	(0.05)
N	4017	2515	2323	3737	2682	2424
R-Squared	0.83	0.86	0.85	0.53	0.53	0.53
Control Group Mean	15.70	16.10	16.00	0.20	0.22	0.20
Infrastructure	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.

Historical density

Table A7 explores the role of pre-KIP population density, one of the criteria in the scoring rule. We observe 1960 population at the locality level from the Census. We match it to localities today using names and historical maps and obtain population density. Then, we define a dummy for localities in the top two densest quintiles.

Column 2 shows that historically denser places have persistent negative impacts on land values today (-13 log points) but less influence on the KIP coefficient, which remains stable around -34 log points with or without controlling for historical density. Since historical density is defined at the locality level, we can only include fixed effects at the sub-district level (larger than localities). In column 3, we show we can recover a 9 log point effect using our baseline specification (with controls and hamlet fixed effects). This is slightly different from the 11 log point effect of the the full sample specification in Table 2, because we lost 4307 observations which cannot be matched with historical density. For heights (columns 3 to 6), the coefficient for KIP is similar with or without the dummy for pre-KIP density and column 6 recovers a similar 7 p.p. effect as we do above. The direct effect of pre-KIP density on heights is positive (column 2) most likely because those dense places are central and tend to have tall buildings.

Table A7: Effect of KIP on land values and heights, controlling for historical density

Dependent variable:	**Log land values**			**1(Height>3)**		
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.34***	-0.33***	-0.09**	-0.08***	-0.08***	-0.07***
	(0.07)	(0.07)	(0.04)	(0.01)	(0.01)	(0.01)
1(High Pre-KIP Density)		-0.13*	.		0.04*	.
		(0.07)			(0.02)	
N	15541	15541	15541	14980	14980	14980
R-Squared	0.57	0.58	0.83	0.15	0.15	0.35
Control Group Mean	15.80	15.80	15.80	0.17	0.17	0.17
Infrastructure	N	N	Y	N	N	Y
Topography	N	N	Y	N	N	Y
Landmarks	N	N	Y	N	N	Y
Geography FE	Sub-district	Sub-district	Hamlet	Sub-district	Sub-district	Hamlet

* 0.10 ** 0.05 *** 0.01

Notes: Each observation is a locality. Controls are averaged at the locality level. Standard errors clustered by locality.

Crowding over time

Table A8 examines the decadal effect of KIP on log density. We collect Census population data for 1980, 1990, 2000, and 2010. We could not find data for 1970. The data is at the locality level and we matched it to our current geographies using the same approach used for the 1960 data. A majority of the localities are in at least 2 or 3 decades. We lose 13 observations because of outliers or failure to match localities across decades (some localities are split and the names are difficult to match). We pooled these repeated cross-sections of localities from 1980 to 2010, obtaining 712 locality-by-decade observations.

Our key regressor *Share KIP* is the area share of a locality that is in KIP, based on our policy maps, expressed as standard deviations within the estimation sample. Column 1 shows that a 1 standard deviation increase in the share of KIP (0.28) is associated with a 31 log points increase in population density in 1980, controlling for 1960 (pre-KIP) population density. The coefficients tend to increase in magnitude as we consider years 1990, 2000, and 2010, consistent with density increasing more over time in KIP. However, we caution that the coefficients are not statistically different. Because the historical population data is only available at the relatively coarse locality level, we can only control for sub-district by decade fixed effects. We also include our baseline controls aggregated at the locality level and interacted with decade fixed effects. In column 2, we find similar patterns considering as dependent variable a long difference relative to 1960 (e.g. log population density in 2010 minus log population density in 1960), instead of controlling for 1960 density. The patterns are similar. Overall, we cannot find conclusive evidence of sharp increases in crowding using this historical density data, but we concede that our conclusions of whether KIP caused crowding may change if our data were more granular and less noisy.

Table A8: Density by decade

Dependent variable:	**Level**	**Change in log**
	(1)	(2)
Share KIP x 1980	0.33***	0.30*
	(0.09)	(0.17)
Share KIP x 1990	0.37***	0.34**
	(0.09)	(0.17)
Share KIP x 2000	0.41***	0.39***
	(0.08)	(0.14)
Share KIP x 2010	0.40***	0.39***
	(0.07)	(0.14)
N	712	712
R-Squared	0.82	0.68
Control Group Mean	8.64	8.64
Infrastructure	Y	Y
Topography	Y	Y
Landmarks	Y	Y
Geography FE	Locality by decade	Locality by decade

* 0.10 ** 0.05 *** 0.01

Notes: Each observation is a locality-decade. Standard errors are clustered by sub-district (one level above locality).

Historical land institutions

In Table A9, 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 through 3 (4 through 6) consider log land values (the height indicator). Reassuringly, the coefficients are similar to our baseline ones.

Table A9: Robustness to excluding Dutch areas

Dependent variable:	**Log land values**			**1(Height>3)**		
Sample:	Full Sample	Historical Kampung	BDD 200m	Full Sample	Historical Kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.14***	-0.16***	-0.15**	-0.12***	-0.07***	-0.10**
	(0.05)	(0.03)	(0.07)	(0.02)	(0.02)	(0.04)
N	1885	14758	2945	5240	18916	4037
R-Squared	0.72	0.82	0.88	0.29	0.35	0.52
Control Group Mean	16.03	15.85	16.07	0.24	0.17	0.19
Geography FE	Locality	Hamlet	KIP Boundary	Locality	Hamlet	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.

Endogenous sorting

Educational attainment Table A10 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 A11 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 A10: 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
Control Group Mean	0.76	0.58	0.19	10.40
Infrastructure	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.

Migration Table A12 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 5-year migrants (columns 1 and 2) and that, if anything, migrants have more education (columns 3 and 4).

Table A11: 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
Control Group Mean	0.78	0.62	0.20	10.60
Infrastructure	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 A10, but restricting the sample to individuals above age 25 born in the same district of residence. Standard errors are clustered by locality.

Table A12: 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	8629812	8629812	2788037	339213
R-Squared	0.14	0.50	0.10	0.11
Control Group Mean	0.46	0.17	10.30	10.70
Infrastructure	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 A13 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 6, with the dependent variable being the average household size in a hamlet. The next two columns present individual-level specifications similar to Table A12, 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 A13: Differences in household size, mortality, and fertility

Dependent variable:	**Household size**	**Nr 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
Control Group Mean	3.96	18.30	2.46
Infrastructure	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.

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 A14, we show that the results for building heights are similar if we drop pixels with no buildings (columns 1 through 3) 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 4 through 6). Our results are similar if we include all the observations but add controls for being close to historical roads and if we restrict the sample to pixels in places that are zoned for commercial developments, based on digital zoning maps provided by the Jakarta City Government.

Table A14: Selection for building heights

Dependent variable:	**1(Height>3)**					
Sample:	Full Sample	Historical Kampung	BDD 200m	Full Sample	Historical Kampung	BDD 200m
	(1)	(2)	(3)	(4)	(5)	(6)
KIP	-0.08***	-0.12***	-0.11***	-0.09***	-0.13***	-0.12**
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.05)
N	17298	5081	3934	9840	3617	2703
R-Squared	0.38	0.30	0.54	0.40	0.32	0.55
Control Group Mean	0.21	0.26	0.24	0.26	0.30	0.28
Infrastructure	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	N	Y	N	N	Y
Exclude no building pixels	Y	Y	Y	N	N	N
Only pixels near predetermined roads	N	N	N	Y	Y	Y
Geography FE	Hamlet	Locality	KIP Boundary	Hamlet	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.

Selection bias for assessed land values

Below we address the concern that KIP areas are more likely to be informal today and property data for informal settlements are less likely to be reported. Table A15 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.

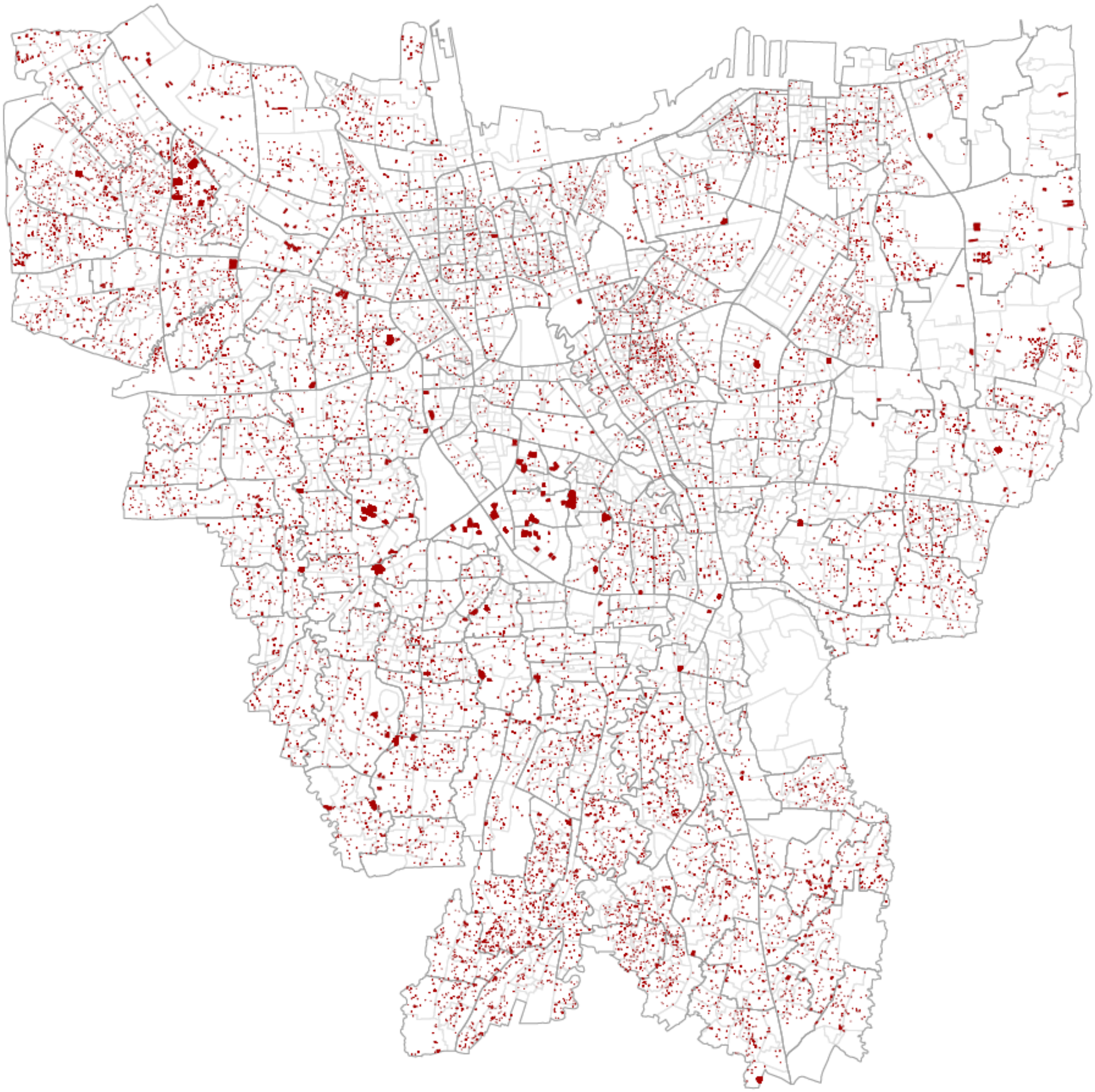
Table A15: Selection for assessed land values

Dependent variable	**1(Has assessed values)**	
Sample	Full Sample	Historical Kampung
	(1)	(2)
KIP	0.03***	0.04***
	(0.005)	(0.009)
N	88832	11002
R-Squared	0.09	0.09
Control Group Mean	0.07	0.07
Infrastructure	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.

Appendix Figures

Figure A1: 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 A2 shows the correlation between the log of assessed land values and the log of property transactions prices. Each point represents values per square meter, averaged at the hamlet level. In 2016, we collected and manually geo-referenced 4,000 property transactions prices from Indonesia's largest property website (*www.brickz.id*). Our main results for land values remain similar after dropping hamlets corresponding to the 3 outliers visible in the plot (two on the right and one the left).

Figure A2: Scatterplot of assessed land values and transaction prices

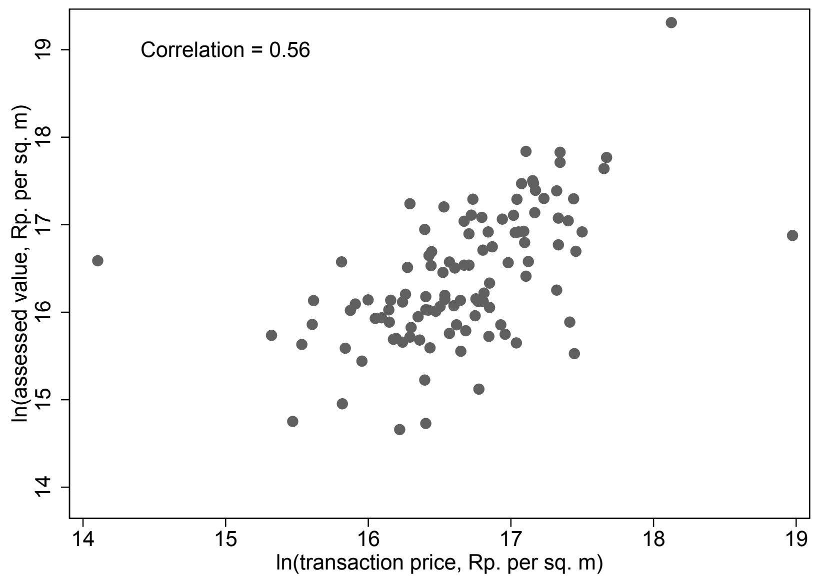
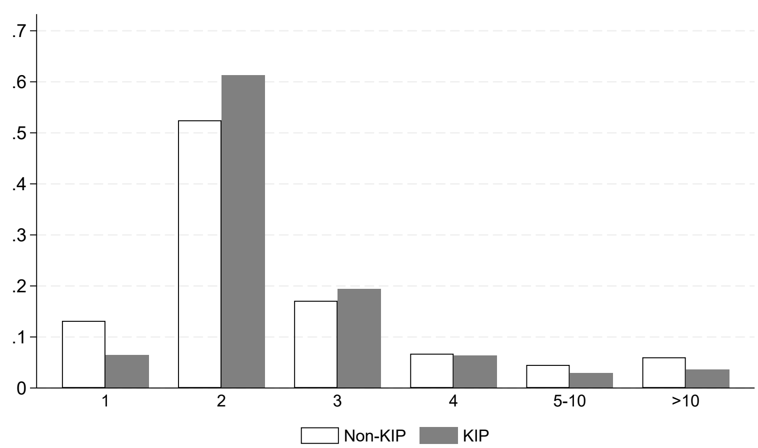


Figure A3 shows non-KIP locations have more tall buildings (white bars at the right tail). Here, we plot the distributions of building heights by KIP status in the photographic sample. KIP pixels (grey bars) are more likely to have shorter buildings whilst non-KIP pixels (white bars) are more likely to have taller buildings.

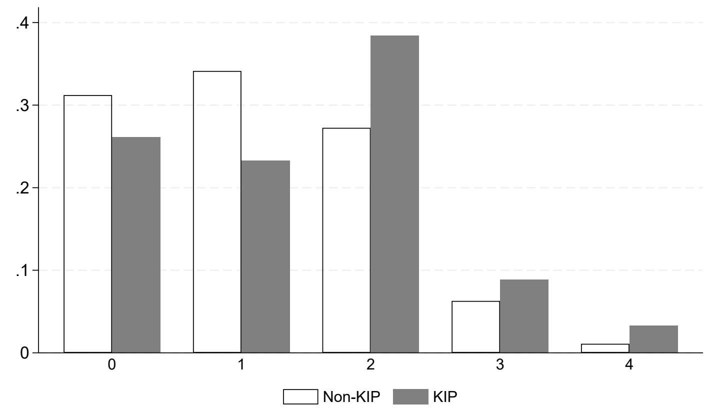
Figure A3: Building heights in KIP and non-KIP



Notes: This bar chart shows the distribution of building heights for the tallest building in KIP and non-KIP pixels in the photographic sample. KIP and non-KIP pixels correspond to grey and white bars, respectively. The horizontal axis represents the number of floors. The vertical axis reports the share of pixels by KIP status. By KIP status, the shares add to one.

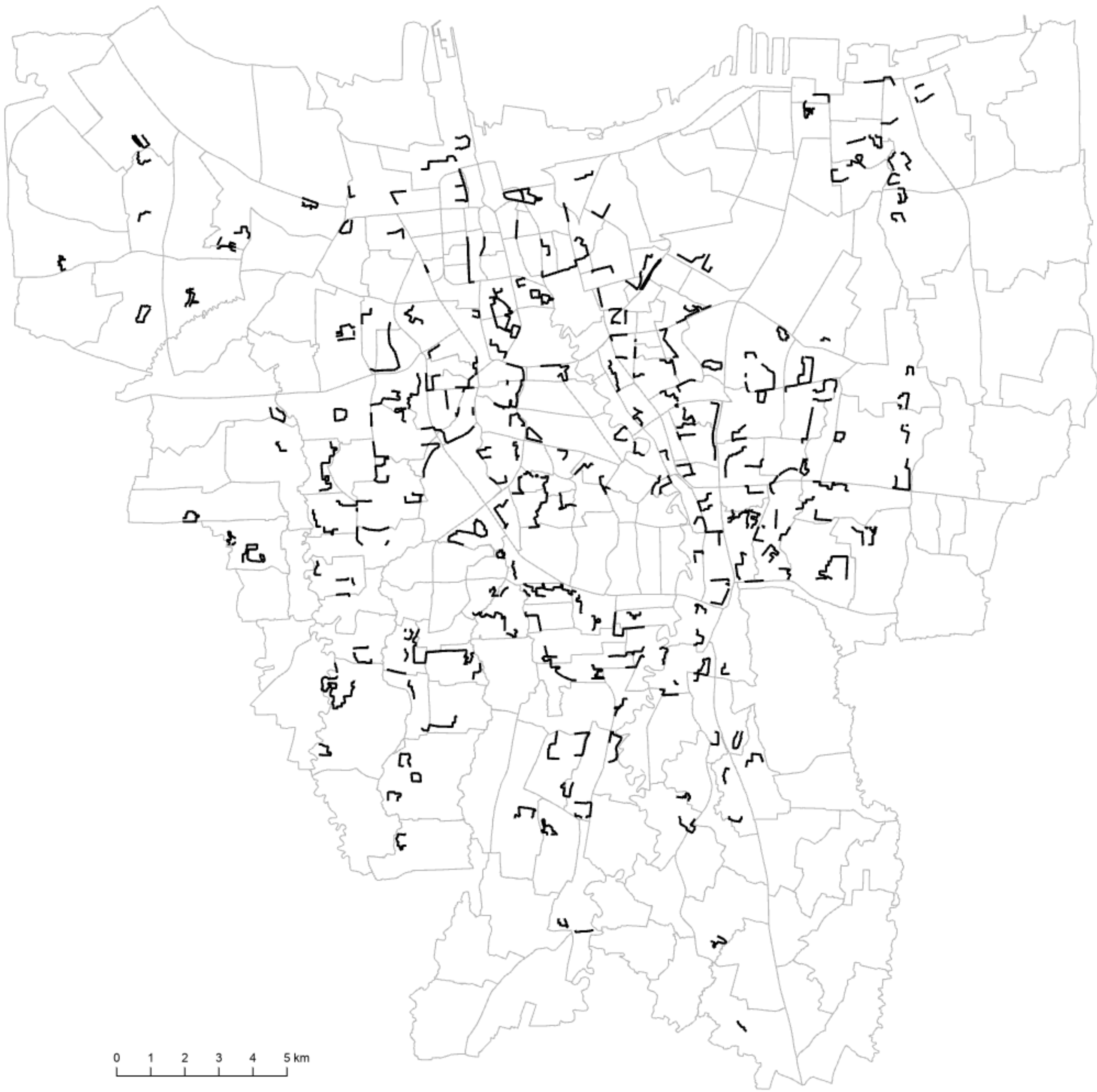
Figure A4: Examples of coding of the rank-based informality index

Figure A5: Rank-based informality index in KIP and non-KIP



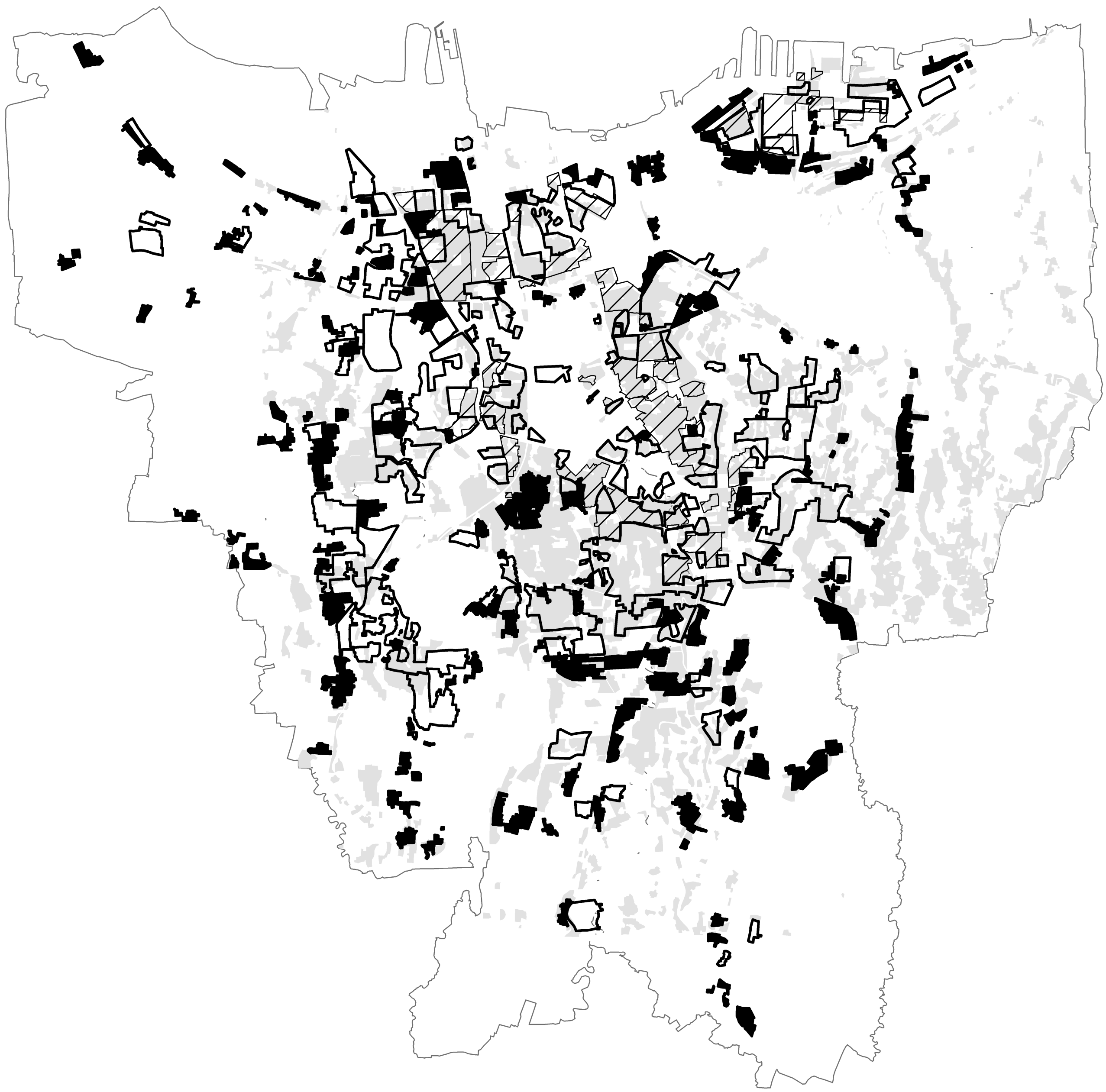
Notes: Distribution of the rank-based informality index by KIP status for the full sample of 19,515 pixels. Index values range from 0, corresponding to "very formal", to 4, corresponding to "very informal". The gray and white bars correspond to KIP and non-KIP pixels, respectively. The vertical axis indicates the share of the pixels by KIP status with each of the two groups (summing to 1). There is a sub-sample of 7,101 pixels where two research assistants ranked all pixels. We give each research assistant a weight of 0.5 for those pixels and a weight of 1 for pixels ranked by only one research assistant.

Figure A6: Map of KIP boundary segments



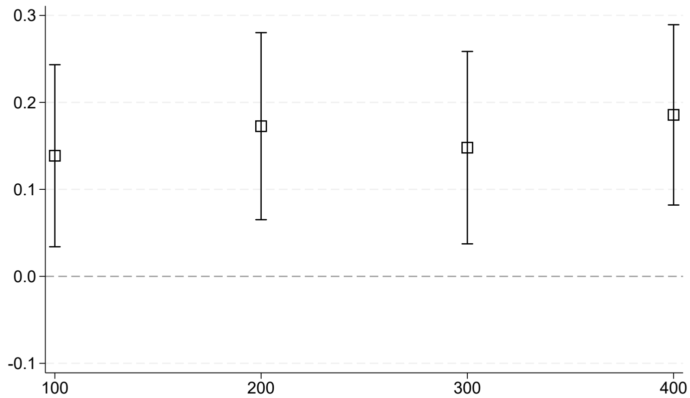
Notes: Map showing 309 KIP boundary segments selected for the BDD design for the photos sample. There are 215 segments in the sub-block analysis.

Figure A7: Map of KIP waves

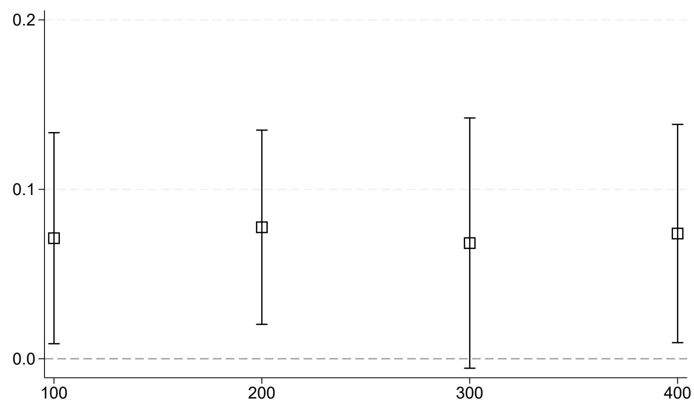


Notes: Map showing areas treated as part of the 3 KIP *Pelita* waves. Striped, hollow, and black areas were respectively exposed to KIP wave I, II, and III. Historical slums are shown in grey.

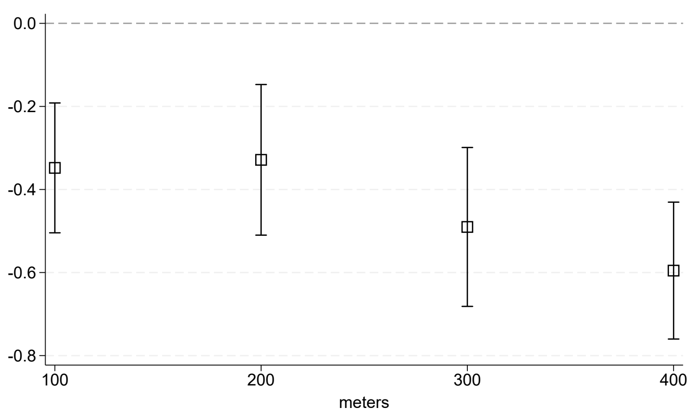
Figure A8: Spatial decay: Distance from non-KIP slums



(a) Log land values



(b) Log height



(c) Log parcel density

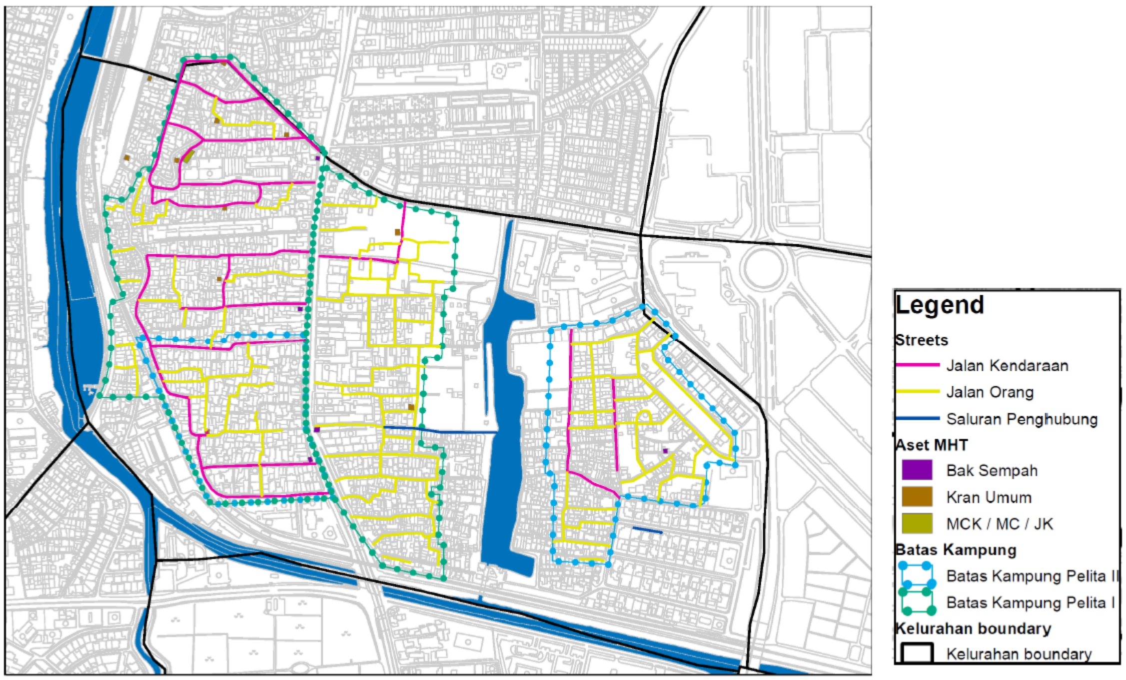
Notes: We investigate the spatial decay pattern of land values away from the boundaries of 45 high-density, informal, and non-KIP hamlets. Specifically, these hamlets do not belong to KIP, have population density above the median, and appear as kampungs as per our photo survey (rank-based index values greater than 1). We estimate spatial decay patterns by exploring heterogeneous effects by distance. We employ a similar specification as our BDD analysis in Table 2, replacing distance to the slum boundary with dummies for different 100m-wide distance bins.

Data Appendix

Program boundaries

Policy maps Our source for KIP program boundaries is a 2011 publication by the Jakarta Department of Housing (DPGP, 2011), consisting over 200 physical maps with a detailed indication of KIP boundaries and investments. One of the goals of the publication was to make a detailed inventory of KIP investments in Jakarta. Ground surveying was performed by the Jakarta Department of Housing mapping team to ensure accuracy. We were given access to the digital files that form the basis of these maps, achieving a 1:5000 meter scale or a resolution of 2.5 meters. These maps 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).

Figure A9: 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.

Boundary selection procedure 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 thus implement an automated procedure to select "clean" treatment and control observations on either side of the KIP boundary.

We begin by splitting KIP polygons into boundary segments by overlaying a fishnet of 500 by 500 meter grid cells to cover all KIP polygons. We use this fishnet to arbitrarily subdivide KIP polygons into boundary segments. We then assign a unique boundary identifier to each segment, which defines our boundary fixed effects. For each observation (pixel or sub-block), we calculate the distances to the nearest and second nearest KIP boundary segment. We use as "control" in our BDD specification any observation that is (a) not in a KIP polygon; (b) within 200 meters of the nearest KIP boundary segment; (c) at a distance greater than 200 meters from the second nearest boundary segment (to avoid contamination). We also explore robustness using other distance cutoffs.

The final sample resulting from this procedure includes 215 (309) boundary segments for which we have assessed land values (building heights) on both sides of a selected KIP boundary segment. Figure A6 shows these 309 boundary segments. From the maps, the boundaries appear evenly distributed throughout Jakarta. Moreover, the control group means of our primary outcomes are close to those in the full sample: the mean for log land values is 15.84 in the full sample and 15.82 in the BDD sample; the mean height is 3.3 floors in the full sample and 3.6 in the new BDD sample. As shown in Table 1, the covariates are balanced across boundary segment fixed effects.

We also explored robustness to the details of the automated procedure, considering various ways to construct the fishnet and obtain different sets of arbitrary boundary segments. For example, we considered a coarser 1000 m fishnet. Additionally, we perturbed the centroid of the fishnet grid and rotated the angle of the fishnet. In all cases, the coefficients of our main outcomes fall within the 95% confidence interval of the baseline estimates. We follow a similar procedure to select clean placebo boundaries for the test discussed in Section 8.2.

Market prices

We compare assessed land values with real estate 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 the rank-based index and number of floors from this sample. Additionally, for a sub-sample of 7,101 pixels, we manually review the appearance of the photos further and code the attribute-based informality index. This sub-sample includes 5,000 pixels from the historical kampung sample and 2,500 from a 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 centroid of pixels to be surveyed and instructed them to take four photographs from the North, South, East, and West angles, from as close as possible to the exact coordinates. We showed them photos from Google Street View as examples. We verified the accuracy of the location from GPS coordinates attached to the photos. In those few cases in which the enumerators could not reach the exact location due to buildings, walls, or roads blocking the access, we used the closest available Street View photos. Results are similar if we drop these photos.

Building height We instructed our research assistants to count the number of floors of the tallest building within the pixel, as seen in the photos. Tall buildings visible in the photos but located outside of the 75-meter pixel were not considered. When uncertain, research assistants used Google Maps to determine whether a building fell within the pixel. For locations surveyed on the field, enumerators were provided with a rule of thumb of a maximum distance of 50 steps. For tall buildings where the total number of floors was not easy to count from the ground, number of floors were recovered from the building's website, from the leasing office or concierge, or on the field checking the elevators.

Rank-based informality index We trained our research assistants to rank photos on a scale ranging from 0 to 4. 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, which we gave as an example to our research assistants. 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. The 7,101 subsample was ranked independently by two research assistants from Jakarta. The correlation between the two research assistants' rankings is 0.78. The remaining photos were ranked by a single research assistant. We consider an average of their two rankings in our analyses, but results are robust to different aggregation approaches and research assistant fixed effects to account for subjective differences.

Attributes-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. This 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.

Figure A10: Example of cadastral map of land parcels

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

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 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 U.S Army map, log average distance to historical railway and tram stations (identified from the 1887 map above and maps from 1914 and 1935 (Topographische Inrichting Batavia, 1914, Allied Geographical Section, 1935)) and the presence of historical wells or pipes within 1000 meters (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 U.S Army map.

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 et al. (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 (e.g. hamlets) and current roads are drawn from OpenStreetMap.

The cadastral maps we use to measure land fragmentation are drawn from the website of the Jakarta Regional Disaster Management Agency. Figure A10 shows an example for one sub-district. The solid red boundaries indicate KIP treated areas.

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

Geographic Units

Below we list the spatial units we refer to in our analyses, along with their total number across the city and average area size.

Table A16: Geographic units

Geographic Unit	Total Number in Jakarta	Average Area
District (*Kabupaten*)	5	129 sq km
Sub-district (*Kecamatan*)	42	15 sq km
Locality (*Kelurahan*)	262	2.5 sq km
Hamlet (*Rukun warga*)	2,606	0.25 sq km
Pixel	19,151	5,600 sq m
Sub-block	19,848	970 sq m

Model Appendix

B.1 Additional theoretical derivations

B.1.1 Residents' problem

Conditional on moving to the city, residents make three sequential choices: (i) where to live (i) (ii) where to work (j) and (iii) how much housing to consume, subject to two idiosyncratic residence- and workplace-specific taste shocks.
The utility of individual ω of type g choosing to live in i and work in j is:

$$U^g_{ij\omega} = (u_{ig})^{\rho^g} \left(\frac{c^g_i}{\beta^g}\right)^{\beta^g} \left(\frac{l^g_i}{1-\beta^g}\right)^{(1-\beta^g)} \varepsilon^g_{i\omega} \upsilon^g_{j\omega} \tag{B.1}$$

where c^g_i denotes a numéraire good (priced at 1) and l^g_i is housing of type g (priced at r^g_i per unit).
Utility shocks $\varepsilon^g_{i\omega}$ and $\upsilon^g_{j\omega}$ capture residents' idiosyncratic preferences for each residence i and workplace j. They are sequentially drawn i.i.d from a Fréchet distribution with scale 1 and shape θ. As shown in Tsivanidis (2023), the alternative assumption of a simultaneous choice of the pair (i, j) yields very similar equations. We set $\theta = 3$ from Tsivanidis (2023).[35]
The problem is solved by backward induction.

Individual housing demand. Conditional of the choice of (i, j) and denoting income with Y^g_{ij}, resident's demand for housing floorspace is

$$l^g_{ij} = \frac{(1-\beta^g)Y^g_{ij}}{r^g_i}. \tag{B.2}$$

Plugging (B.2) into (B.1) yields indirect utility (equation 2 in the paper). We set $\beta^H = (1-0.17)$ and $\beta^L = (1-0.13)$ to be consistent with the housing expenditure share for households above and below median income respectively in the Indonesian SUSENAS household survey.

Workplace choice In the second step, residents choose where to work, conditional on their choice of where to live.
An individual of group g living in i and working in j supplies inelastically one unit of labor and earns labor income $\frac{w^g_j}{d_{ij}}$, where d_{ij} reflects commuting costs from location i to location j. The latter are parameterized as $d_{ij} = exp(-\rho t_{ij})$, where t_{ij} are commute times. We compute commute times using a speed of 25 km per hour and set $\rho = 0.01$, the value estimated by Tsivanidis (2023) for Bogotá.
For a given draw $\varepsilon^g_{i\omega}$ and choice of residence, a resident chooses j to maximize $U^g_{j\omega|i}$. The latter is Fréchet distributed with scale $\Phi^g_{j|i}$ and shape θ, where

$$\Phi^g_{j|i} = \left(\varepsilon^g_{i\omega}(u^g_i)^{\rho^g}(w^g_j/d_{ij})(r^g_i)^{\beta^g-1}\right)^{\theta}. \tag{B.3}$$

By standard Fréchet properties, conditional on having chosen to live in i, the likelihood of working in j is

$$p^g_{j|i} = \frac{\Phi^g_{j|i}}{\sum\limits_j \Phi^g_{j|i}}. \tag{B.4}$$

Following Tsivanidis (2023), we define residential market access in neighborhood i as $RCMA^g_i \equiv \sum_j \left(\frac{w^g_j}{d_{ij}}\right)^{\theta}$. Equation B.4 can be rearranged as

[35] We assume θ is the same for both groups and draws. An earlier version of Tsivanidis (2023) estimates the shape parameter for a model with sequential draws from two distinct distributions and separately for high- and low- skilled households in Bogotá. These distinct parameters are all close, ranging from 2.7 to 3. Our results are very similar if we allow for θ to vary by group and draw using those parameter values.

$$p^g_{j|i} = \frac{\left(w^g_j/d_{ij}\right)^{\theta}}{\text{RCMA}^g_i}. \tag{B.5}$$

The expected labor income earned by residents of neighborhood i can be calculated as:

$$\overline{w}^g_i = \sum_j p^g_{j|i} \cdot \mathbb{E}\left(\frac{w^g_j}{d_{ij}}\middle| j \text{ was chosen}\right).$$

By Fréchet properties,

$$\mathbb{E}\left(\frac{w^g_j}{d_{ij}}\middle| j \text{ was chosen}\right) = \widetilde{\Gamma} \cdot \left[\sum_j \left(\frac{w^g_j}{d_{ij}}\right)^{\theta}\right]^{\frac{1}{\theta}} = \widetilde{\Gamma} \cdot \text{RCMA}_i^{\frac{1}{\theta}}$$

with $\widetilde{\Gamma} = \Gamma\left(\frac{\theta-1}{\theta}\right)$, which yields $\overline{w}^g_i = \widetilde{\Gamma}\text{RCMA}_i^{\frac{1}{\theta}}$. This term summarizes job access from neighborhood i.
Once location choices have taken place, each resident additionally receives an equal share of the total land rents collected in the city within their group, as a lump sum $\overline{r}^g$. This is determined in equilibrium but taken as given by households. Total realized income is thus $\overline{Y}^g_i = \overline{w}^g_i + \overline{r}^g$.

Location choice In the first step, residents choose the location of residence i, for given $\overline{Y}^g_i$, to maximize

$$U^g_i = (u^g_i)^{\rho^g} (\overline{Y}^g_i) \left(r^g_i\right)^{\beta^g - 1} \varepsilon_i. \tag{B.6}$$

By standard Fréchet properties, the ex ante expected utility in the city is

$$\overline{U}^g = \widetilde{\Gamma}\left[\sum_i \left((u^g_i)^{\rho^g} (\overline{Y}^g_i) \left(r^g_i\right)^{\beta^g-1}\right)^{\theta}\right]^{\frac{1}{\theta}} \tag{B.7}$$

and the share of group g residents residing in i is

$$p^g_i = \frac{\left[(u^g_i)^{\rho^g} (\overline{Y}^g_i) \left(r^g_i\right)^{\beta^g-1}\right]^{\theta}}{\sum_i \left[(u^g_i)^{\rho^g} (\overline{Y}^g_i) \left(r^g_i\right)^{\beta^g-1}\right]^{\theta}}.$$

Open city The total measure of residents in Jakarta is pinned down by the mobility condition on p. 27. The latter can be derived from a model in which households choose whether to move to the city or stay in the outer economy (Sturm et al., 2023). We calibrate $\tilde{U}^g$, the utility in the rest of the economy from the baseline initial utility in the city and the population counts of the economy as a whole:

$$\tilde{U}^g = \left(\frac{\overline{L}^g_{\text{econ}}}{\overline{L}^g} - 1\right) \cdot \overline{U}^g \tag{B.8}$$

We consider Jabodetabek (greater Jakarta) as the broader economy, setting the total population to $\overline{L}^H_{econ} + \overline{L}^L_{econ} = 9.8$ million households. Jakarta comprises 33% of the Jabodetabek population. We set the share of H types in the outside economy to be 0.21, matching the high school completion rate for the districts in Jabodetabek that are not Jakarta, from the 2010 Census.

B.2 Additional estimation details

B.2.1 Data preparation

Below we describe how we assign formal and informal land use shares (λ^g_i), rents (r^g_i), and population, (L^g_i) to non-KIP locations using our data. Our starting data includes assessed land values at the sub-block level, building heights at the pixel level, and population at the Census block level. None of these data are disaggregated by formal or informal status. The key data preparation steps thus involve: (i) assigning non-KIP observations to formal (H) or informal (L); (ii) converting land values to rents; (iii) aggregating at the region level, where regions are defined by distance bands to the CBD.

Land use shares We begin by classifying pixels in our core dataset as formal (H) or informal (L) based on parcel count, where pixels in the top quartile of the Jakarta-wide distribution by parcel count are considered informal. Of our various metrics of informality, parcel count is that with the most comprehensive coverage. We average this binary indicator among non-KIP pixels in each region and obtain λ_i^L. On average, the formal land share in non-KIP is 81%.

Heights We set informal heights h^L to be 1 everywhere. For formal heights h^H, we use building heights observations in non-KIP pixels classified as H with the procedure above and average them within regions.

Rents First, we match sub-blocks to pixels to identify H and L land value observations. To address outliers in the data, we winsorize land values as a preliminary step (1%) before assigning them to H or L, and we winsorize informal land values one more time (5%) as they are considerably noisier.

Second, we use these land values along with heights to calculate formal and informal rents. To convert land values into floorspace prices r^g, we use the assessment approach of the Indonesian Land Agency, whereby the total value of floorspace per unit of land comprises the value of the land and value of the structures. Denoting heights as h^g, construction costs per square meter of built-up space as c^g and the share of a plot that is built up as Sh^g:

$$r^g \cdot h^g \cdot Sh^g \cdot = v^g + c^g \cdot h^g \cdot Sh^g. \tag{B.9}$$

We apply this formula at the hamlet level for the H observations, and then average at the region level. For L observations, which are noisier, we implement this calculation at the region level. As Sh we use the average built up share by non-KIP region based on our cadastral maps (on average, 35%). Construction costs c^g are set based on industry reports. For formal construction, we consider USD \$1000 per squared meter in the center (reflecting higher quality of buildings in the center) and \$422 in the rest of the city. For informal construction, we consider \$195 per square meter ((Nurdini et al., 2017, ARCADIS, 2019)). We then express the price of floorspace as annual rents by applying a capitalization rate of 4.3% based on the 2000-2015 average real interest rate (inflation adjusted) in Indonesia from the World Bank.

Population We aggregate population counts at the region level from block-level Census data and disaggregate by H and L types using individual household characteristics.

As a preliminary step, we exclude non-residential parts of Jakarta. Absent comprehensive zoning data, we identify areas of the city that are not residential as areas with very low population density (less than 20 households per squared km). We calculate average population density in residential blocks in each neighborhood and then multiply it by total residential land to obtain population totals.

In order to determine H and L population shares in each neighborhood, we predict the likelihood of living in an informal area (defined by parcel count as above) based on individual characteristics from the Census. Specifically, we include age, gender, education, marital status, migrant status, and being economically active.[36] Our predictive regression is at the hamlet level and controls for zoning in addition to our baseline set of controls. We then rescale these probabilities proportionally so as to target a city-wide share of H types of 75%.

B.2.2 Model parameters

Amenities We identify amenities (up to a group-specific normalizer) from the neighborhood choice condition:

$$\frac{u_i^g}{u_j^g} = \left[\left(\frac{L_i^g}{L_j^g} \right)^{\frac{1}{\theta}} \left(\frac{r_i^g}{r_j^g} \right)^{1-\beta^g} \left(\frac{Y_j^g}{Y_i^g} \right) \right]^{\frac{1}{\rho^g}}. \tag{B.10}$$

[36]While the US literature typically considers education levels as a way to define H and L groups, in Jakarta, kampung and formal residents have comparable levels of education. As a reference, Gechter and Tsivanidis (2023) use last names and caste to distinguish formal and informal residents.

We normalize amenities setting $u^g_{Outer} = 1$ where $Outer$ denotes the outermost (non-KIP) region in Jakarta.
We then retrieve the exogenous component $\overline{u}^g_i = u^g_i \left(\frac{L^H_I}{L^H_I + L^L_I}\right)^{-\mu^g}$.
Following Gechter and Tsivanidis (2023), we normalize $\rho_L = 1$ and set $\rho^H = 1.44$ and we set $\mu^H = 0.88$, as per their Mumbai estimates. At baseline, we set $\mu^L = 0.3\mu^H$ reflecting the fact that L types may not benefit as much from H-share spillovers. This is in line with the standard treatment of endogenous amenities across high- and low-skilled in the U.S. literature (Diamond (2016), Su (2022)). Since this parameter is important for the overall size of the gains and is not one where the literature on developing countries is resolved, we perform a robustness exercise considering different values (Section 7.6).

Formalization cost: τ_i is pinned down by relative profits and land shares, rearranging (7):

$$\tau_i = 1 - \left(\frac{\lambda^H_i}{\lambda^L_i}\right)^{1/\gamma} \cdot \frac{\pi^L_i}{\pi^H_i}. \tag{B.11}$$

Housing supply parameters We set the cost elasticity with respect to heights as $\nu = 1.69$, estimated by Sturm et al. (2023) for Dhaka, which implies a housing supply elasticity of $\frac{1}{(\nu-1)} = 1.45$. This is in the ballpark of similar estimates for developed and developing countries.[37]
For our robustness exercise where we allow for elastic informal heights in the counterfactual, we set $\frac{1}{(\nu_L-1)} = 1.3$ following Henderson et al. (2020), implying $\nu_L = 1.77$.
We retrieve k_i from the observed heights and rents from equation (10). Finally, we calibrate T^g_i to clear the floorspace markets (equation (11)).
We set the fixed cost of informal construction $\bar{c}^L = 200,000$ Rupiahs (USD $12) per squared meter.
We set $\phi^L = 0.5$ and $\phi^H = 0.3$ reflecting the average share of pixels built-up in each neighborhood as per our cadastral maps. These figures are similar to those found by Henderson et al. (2020). for slums and formal areas in Nairobi.

Residential Commuter Market Access We follow the procedure in Tsivanidis (2023) to estimate $\overline{w}^g_i$ from employment and population counts.
Define Firm Commuter Marke Access $FCMA^g_j \equiv \sum_i \left(\frac{u^g_i (r^g_i)^{\beta^g - 1}}{d_{ij}}\right)^\theta$. This captures access to workers from workplace location j. Denote employment in j as $L^g_{Fj} \equiv \sum_i p_{j|i} \cdot L^g_i$. This can be rewritten as $L^g_{Fj} = \sum_i \frac{\left(w^g_j / d_{ij}\right)^\theta}{\text{RCMA}^g_i}$. Tsivanidis (2023) shows that $RCMA^g_i$ and $FMCA^g_j$ are linked through the following system of equations:

$$\begin{cases} \text{RCMA}^g_i & = \sum_j \frac{L^g_{Fj}}{d^\theta_{ij}} \cdot \frac{1}{\text{FCMA}^g_j} \\ \text{FCMA}^g_j & = \sum_i \frac{L^g_i}{d^\theta_{ij}} \cdot \frac{1}{\text{RCMA}^g_i}. \end{cases}$$

Using employment (L^g_{Fj}) and population (L^g_i) counts, the system of equations above can be solved for RCMA^g_i, up to a group-specific constant.
We implement this calculation using population counts from the Census and employment counts from the 2010 Japan International Cooperation Agency (JICA) commuter travel survey (Gaduh et al., 2022)[38], both at the locality level. This high resolution allows us to capture spatial labor market linkages in a granular way and calculate RCMA at the locality level. We then embed RCMA in our coarser, region-level model by averaging it across regions. This is equivalent to a model in which residents choose a region first, then are randomly allocated to a locality within a region, then choose in which locality to work and commute to (Kreindler and Miyauchi, 2023).

[37] Henderson et al. (2020) estimate parameters that yield an elasticity of 1.4 (1.3) in the formal (informal) sector for Nairobi. In the US, Saiz (2010) finds estimates between 1.2 and 2.6, with an average of 1.75. Heblich et al. (2020) estimates an elasticity of 1.8 for 1800's London.
[38] We thank Gaduh et al. (2022) for kindly sharing their code.

Slum conversion elasticity There is no guidance in the literature on plausible values for the profit shock dispersion parameter γ, which governs the slum conversion elasticity. At baseline, we estimate it leveraging reduced-form variation from KIP in the formal rents and informal land shares, then we consider robustness to a wide range of values. Reassuringly, our results are very similar.

Taking logs of the land shares equation (7) yields:

$$\log \lambda^L = \gamma \log\left(\pi^L\right) - \log\left[(1-\tau)^\gamma \left(\pi^H\right)^\gamma + \left(\pi^L\right)^\gamma\right]$$

The cross-elasticity of the informal land share to formal rents is:

$$\frac{\mathrm{d}\log\lambda^L}{\mathrm{d}\log r^H} = -\frac{(1-\tau)^\gamma \gamma \left(\pi^H\right)^{\gamma-1}}{(1-\tau_i)^\gamma \left(\pi_i^H\right)^\gamma + \left(\pi_i^L\right)^\gamma} \cdot \frac{\mathrm{d}\pi^H}{\mathrm{d}\log r^H}$$

yielding

$$\gamma = -\frac{\mathrm{d}\log\lambda^L}{\mathrm{d}\log r^H} \cdot \frac{1}{\lambda^H} \cdot \frac{\pi^H}{h^H \phi^H r^H}.$$

We estimate $\frac{\mathrm{d}\log\lambda^L}{\mathrm{d}\log r^H}$ from $\frac{\frac{\mathrm{d}\log\lambda^L}{\mathrm{d}KIP}}{\frac{\mathrm{d}\log r^H}{\mathrm{d}KIP}}$. We consider different regression estimates that yield values of γ greater than 1. As a baseline we set $\frac{\mathrm{d}\log\lambda^L}{\mathrm{d}KIP} = 0.25$ and $\frac{\mathrm{d}\log r^H}{\mathrm{d}KIP} = -0.12$. These are obtained from regressions of informal land shares on KIP at the pixel level, including village fixed effects and from a regression of formal rents on KIP at the hamlet level, including locality fixed effects in the historical sample, both also including our baseline controls. For λ^H, we use the average share of H pixels in our data (0.75). The H profit to revenue ratio ($\frac{\pi^H}{h^H\phi^H r^H}$) in our data is 0.41. This calculation yields $\gamma = 1.18$.

This parameter governs the dispersion of idiosyncratic profit shocks and controls the sensitivity of land shares to formal and informal rents. Lower values (closer to 1) imply greater heterogeneity in profit shocks and less sensitivity in developers' decisions to formalize based on rents. We consider a range of alternative values for γ and find that our results are very similar, both in magnitudes of the overall gains and in the patterns of gains predominantly in the center. Specifically we consider lower values (1.05, 1.1, and 1.15, which all yield overall gains of 3.2%) and higher values (from 1.25 to 3, at 0.25 intervals; all yield overall gains between 2.8% and 2.9%).

B.2.3 Constructing model-generated KIP regions

Below we explain how we use our reduced-form estimates in Table 3 to construct model-generated KIP counterparts for non-KIP regions. Under our identifying assumptions, location quality is assumed to be comparable by KIP status, conditional on controls. This way, through the lens of the model, wedges in land values and heights between KIP and non-KIP locations arise from differences in location fundamentals (τ_i, u_i^g). Our goal is to recover wedges in fundamentals that imply wedges in equilibrium land values and heights that match our reduced-form estimates.

Recall that we observe (λ_i^g, r_i^g, h_i^g) for non-KIP locations (e.g. non-KIP, center) from the data. We implement a procedure to search for values of (λ_i^g, r_i^g, h_i^g) in each corresponding KIP location (e.g. KIP, center) that deliver the wedges in land values and heights from Table 3). The steps are outlined below.

1. We anchor our procedure on the formal land share λ_i^H, which is bounded between 0 and 1. That is, we first pick a value of λ_i^H and recover rents and heights to match the reduced-form moments.
   - Given λ_i^H, for each non-KIP location, we first recover 3 unknowns: rents r_i^g for H and L and the height for H (h_i^H). h_i^L is fixed at baseline given inelastic informal supply.
   - Our reduced-form estimates give us two equations (columns 1 and 3 in Table 3) and we get the third from the first-order condition for H type housing supply. As an example, for the center, the estimates imply land values

are 14 log points lower and heights are 13 log points lower in KIP.

- Given λ_i^H and a fixed h^L, we can recover what h^H has to be in KIP to imply average heights that are lower by 13 log points in the center.
- Similar to Sturm et al. (2023), from the first-order condition for profit maximization, equation (10), there is a 1-to-1 mapping between rents and heights to allow us to infer rents.
- Given λ_i^H and r_i^H, we can recover r_i^L in KIP such that average land values in KIP are lower by 14 log points.
- This way, we used 3 equations to recover 3 unknowns (r_i^g and h_i^H).
- Note that our empirical data corresponds to averages of formal and informal observations. The model analogs of our observed land values and heights are $v_i \equiv v_i^H \cdot \lambda_i^H + v_i^L \cdot \lambda_i^L$ and $h_i \equiv h_i^H \cdot \lambda_i^H + h_i^L \cdot \lambda_i^L$ respectively. Land values v_i^g are converted into space rents r_i^g using construction costs and building heights using the procedure discussed in B.2.1.

2. Having recovered rents and heights, we can infer formalization costs τ_i from equation (7) that governs land use patterns.
3. To recover amenities u_i^g, we use the floor space market clearing condition, equation (11), to back out population counts (given rents, heights, and λ_i^g). Given population counts, we can recover amenities from location choice conditions (equation 9).

With the procedure outlined above, we recover a vector of rents, heights, population counts, formalization costs, and amenities for each λ_i^H, such that the model-implied wedges in equilibrium land values and heights match the wedges from the reduced-form estimates. From this vector, we calculate the differences between the model-implied equilibrium conditions and the empirical moments in the data. In cases with multiple solution vectors, we search for λ_i^H that minimizes the mean-squared error and is greater than λ_i^H in the non-KIP location, consistent with KIP being less formal. This KIP counterpart is our baseline.

For robustness, we also explored counterfactuals using other solution vectors besides the one that minimizes the mean-squared error. Our welfare conclusions are the same.

B.2.4 Model: robustness

Table B.1: Welfare effects of lifting KIP everywhere: robustness

	H	L	All
Open city, spillovers, $\mu^L = 0.3\mu^H$ (baseline)	5.0%	-2.1%	3.1%
Open city, no spillovers	1.3%	-3.6%	0.1%
Open city, $\mu^L = 0.5\mu^H$	4.3%	-1.1%	2.9%
Open city, $\mu^L = 0.7\mu^H$	3.8%	-0.5%	2.6%
Open city, $\mu^L = \mu^H$	3.2%	0.04%	2.3%
Closed city, spillovers	2.3%	-3.2%	0.7%
Closed city, no spillovers	1.3%	-3.9%	-0.2%