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

Mariaflavia Harari[†]
*University of Pennsylvania*

Maisy Wong[‡]
*University of Pennsylvania and NBER*

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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 estimate 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 and address program selection bias through localized comparisons. On average, KIP areas today have lower land values, shorter buildings, and are more informal, per a photographs-based slum index. The negative effects are concentrated within 5km of the CBD. We develop a spatial equilibrium model to characterize the welfare implications of KIP. Counterfactuals suggest that 78% of the welfare effects stem from removing KIP in the center and highlight how to mitigate losses to displaced residents.

**JEL codes: R14, R31, R48**
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[†]Corresponding author. Wharton Real Estate. 428 Dinan Hall, 3733 Spruce Street, Philadelphia, PA 19104-6301. Email: harari@wharton.upenn.edu.

[‡]Wharton Real Estate. 425 Dinan Hall, 3733 Spruce Street, Philadelphia, PA 19104-6301. Email: maisy@wharton.upenn.edu.

# 1 Introduction

Developing countries are expected to undergo massive urban expansion to accommodate two billion more people by 2050 (UN-Habitat, 2022). 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 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, a popular 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 without displacing them. However, policy makers are concerned that upgrading can make slums persist longer than they otherwise would. This can entail significant opportunity costs, especially as cities expand and slums occupy centrally located land (Henderson et al., 2020).

This paper deepens our understanding of slum upgrading and the spatial misallocation of land. Our first contribution is to provide long-term causal impacts of KIP, as modern Jakarta grows out of informality. Second, we combine administrative data and an innovative photographic survey of formal *and informal* housing markets. While KIP planners targeted slums in worse conditions in the 1960's, we address program selection bias using credible research designs. Third, we integrate our reduced-form estimates with a spatial equilibrium model to characterize the welfare implications of slum upgrading, highlighting that the opportunity costs from upgrading and preserving slums are concentrated in central areas.

Our research designs leverage high-resolution policy maps and outcomes from 2015, including 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). Our second specification restricts the sample to historical kampungs that existed before KIP and compares treated ones with those that were not, within the same locality (comparable to U.S. census tracts). Finally, we employ a boundary discontinuity design within 200 meters of KIP boundaries. The identifying assumption is that unobserved quality is comparable across KIP boundaries, conditional on our controls and fixed effects.

[1] Slum upgrading programs have been recently implemented 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.

Our baseline estimates imply that KIP areas have 10% lower land values, -7 percentage points (p.p.) lower likelihood of having tall buildings (more than 3 floors), and buildings with 9% fewer floors. The pattern is robust across all specifications, with effects at least as large as 40% of the control group means. These patterns are consistent with concerns of delayed formalization: while KIP neighborhoods improved after the upgrades (World Bank, 1995), they persisted as slums while non-KIP areas became formal, leading to a reversal in market outcomes.

We establish that KIP places are indeed more likely to be informal today using multiple metrics. We construct an informality index that ranks photos from 0 (very formal) to 4 (very informal) based on neighborhood appearance. KIP areas are more informal by 0.27 units (relative to a control group mean of 1.11). Moreover, KIP areas are also more likely to have parcels that are not registered and more fragmented land, as measured by parcel density.

Importantly, these negative average impacts mask significant spatial heterogeneity, with the largest effects concentrated in central areas, where KIP is prevalent. Intuitively, the opportunity costs from staying informal are greater close to the city center, where the potential gains from redevelopment are the largest. We leverage the geographic scope of KIP, spanning a quarter of Jakarta's land area, and use distance to the central business district (CBD) to classify the city into center, middle, and peripheral regions. The estimates are the most negative in the center, where 44% of all upgraded areas are, followed by the middle and the periphery (-0.14, -0.10, -0.09 for land values and -0.13, -0.06, -0.04 for heights).

We explore several factors associated with delayed formalization in KIP. A key concern of policy makers is that upgrades can make slums attractive, potentially leading to crowding and land fragmentation. Holdout problems can also arise, complicating land assembly. We lack high resolution, time-series data on population density to test whether KIP caused crowding. From an administrative data of cadastral maps, we estimate that KIP areas have 10.13 more parcels per unit area, relative to a mean of 12.8 in the control group. We also find greater household density in KIP.

Moreover, we consider the role of the physical upgrades. We obtained detailed maps of different types KIP investments, including paved and unpaved roads, number of sanitation facilities, and number of public buildings. To quantify exposure effects, we measure proximity to the upgrades and treatment intensity (length of roads per unit area and number of built facilities). We cannot detect differential impacts on land values. This is in line with the 15-year projected useful life of the basic upgrades (Darrundono, 1997).

Our results survive a battery of robustness checks. First, we exploit the staggered roll-out of KIP across three waves to assess program selection bias. We first establish 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.

To characterize the welfare implications of KIP, we develop a spatial equilibrium model along the lines of (Gechter and Tsivanidis, 2023), featuring two types of residents, high- and low-skilled, and 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, captured by a formalization "tax".

Through the lens of the model, wedges in land values and heights between KIP and non KIP arise from differences in amenities and formalization costs. 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. 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.

We then implement counterfactuals to quantitatively assess how KIP affects welfare, accounting for general equilibrium effects and spillovers. As a benchmark, we calculate a city-wide welfare effect of 3.3% 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). Lifting KIP, formal housing supply is boosted, the high-skilled gain while the low-skilled lose as they are displaced to less desirable locations. Echoing the reduced-form results, we find that 78% of the gains in the model are associated with KIP locations in the center. This is because the relative profitability of formal land use and the utility gains for formal residents are the largest in these areas.

Additionally, we provide counterfactuals highlighting the equity/efficiency tradeoffs associated with slum upgrading. For example, we consider a zoning reform bundling the removal of KIP in the center and a relaxation of height restrictions, which preserves the gains to the high-skilled while minimizing displacement of low-skilled. We also show that 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. This suggests that slum upgrading may offer an attractive cost-benefit balance in cities at earlier stages of development, similar to the middle and peripheral areas on Jakarta, where the opportunity costs of staying informal are low. Additionally, we highlight that urban transformation has major distributional implications as the poor are often displaced without compensation.

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.[3] Relative to other policy approaches, slum upgrading can be suitable for cities with limited vacant land and resources to provide shelter at scale. We contribute policy lessons using one of the world's largest slum upgrading programs.

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 measuring urban informality. Our photos-based index overcomes 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.

[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), housing improvements (Galiani et al., 2017), and slum clearance (Rojas-Ampuero and Carrera, 2023). 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.

# 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 it 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.

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

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

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). 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.[6]

## 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 upgrading 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).

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.[7] 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 (Harari and Wong, 2024), 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 negotiations involving developers, residents, government officials, and

[6]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).

[7]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.

middlemen. Local governments fear political backlash from slum clearance, as residents contend that they are not compensated adequately, if at all.[8] 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 number of 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 measures of informality. More details about data sources and processing are provided in the Data Appendix. Table A1 reports summary statistics.

## 3.1 Assessed land values

We observe assessed land values from a 2015 digital map available through the Smart City Jakarta initiative. The Indonesian 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 Rupiahs 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 (see Section 8.4). The average land value is 12 million Rupiahs per square meter (around US$90 per square foot).

[8] 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).

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).

## 3.2 Building heights

We measure building heights from a photographic survey we collected. The unit of observation is a 75 meter-by-75 meter pixel.[9] 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 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 tagged with a 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 hand-coded a rank-based index that provides a holistic assessment of the neighborhood's quality based on photographs. The index ranges from 0 (very formal) to 4 (very informal). Examples can be found in Figure A3. We instructed our research assistants to rank photos based 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).

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

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

and made public by the Indonesian National Land Agency in 2020. 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).

**Population data.** From the 2010 complete count Population Census, we observe demographics for 10 million individuals in Jakarta, including age, gender, educational attainment, and migration status. For the model, we use this data to predict the likelihood that households in formal and informal locations are high versus low types.

## 3.4 Policy maps and historical kampungs

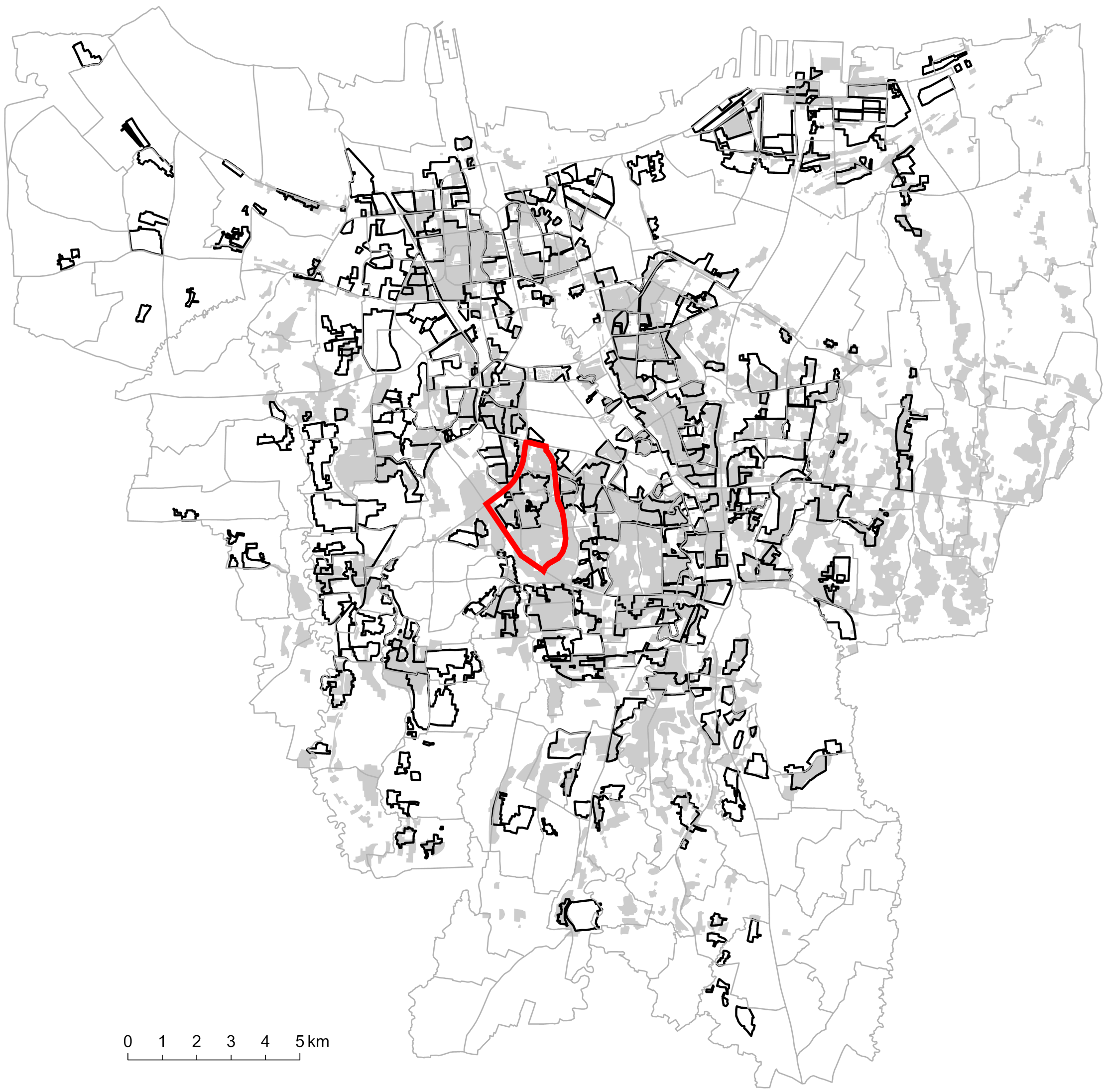
**KIP boundaries.** We utilize high-resolution (2.5 meters) maps from the Jakarta Department of Housing (DPGP, 2011), indicating the boundaries of KIP upgraded areas and the individual assets provided (e.g. roads, sanitation facilities, and community buildings). An example map is provided in Figure A9. 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 A4 shows that the resulting boundary segments are evenly distributed across Jakarta. The Appendix discusses additional details on the selection procedure.

**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.[10] We also use these maps to trace major historical roads.

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

**Figure 1:** KIP boundaries and historical kampungs



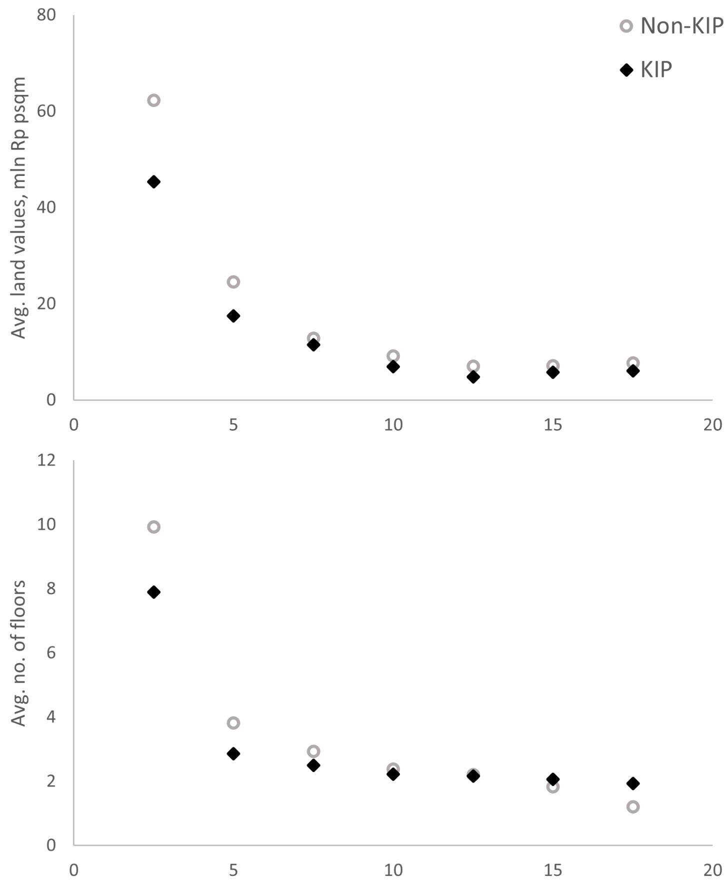

Notes: Map showing KIP boundaries (black border) and historical kampungs that existed before KIP (shaded regions). The grey borders are locality boundaries. The thick red boundary in the middle is the Golden Triangle.

## 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 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.

As CBD, we consider the "Golden Triangle" (red polygon in the map), an approximately 5 squared km area delineated by three road arteries (Bland, 2014). Notably, KIP did not influence

**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).

the location of the Golden Triangle. Even though skyscrapers emerged only several decades later, the roads delineating the Triangle were largely established before KIP.

# 4 Empirical framework

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

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

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

The parameter of interest is $\beta$, 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 $\xi_{ij}$ 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 now have similar quality, conditional on observables and granular fixed effects. We discuss potential confounding due to program selection and persistent pre-KIP differences in Sections 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).[11] 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.[12] Our BDD specification controls for distance to the boundary interacted with KIP, boundary segment fixed effects, and locality 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.[13]

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

[11] A list of all administrative units along with their area size is reported in Table A13 in the Data Appendix.

[12] 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.

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

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.[14] All variables are described in the Data Appendix.

# 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 1 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 A2.

Across all three specifications, KIP areas have lower land values on average. The full sample estimate of -0.11 in column 1 compares observably identical KIP versus non-KIP observations within hamlets. Column 2 restricts the comparison to historical kampungs within the same locality, with a slightly more negative estimate of -0.14. Column 3 presents our BDD analysis showing a coefficient estimate of -0.18 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. This specification uses the full photographic sample for 19,515 pixels. Below, we also consider log of heights, which conditions on a selected

[14]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.

**Table 1:** 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 public parks and roads. All other controls are listed in Table A2. Standard errors are clustered by locality (full and historical specifications), and by KIP boundary (BDD specification).

sample of pixels that have buildings. We add sampling strata fixed effects (from our photographic survey) as well as a dummy for pixels with public parks 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 A5 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% on number of floors (see Table A3).

## 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 that 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.[15] 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 2 presents larger estimated effects for log land values in the center (-0.14), compared to the middle (-0.10) and periphery (-0.09). Columns 2 and 3 present heterogeneous effects for the extensive and intensive margins of building heights. 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 (0.13 estimate for log heights) relative to the middle (0.06) and periphery (0.04). The estimated effects for buildings above 3 floors are even (7, 7, and 6 p.p., respectively).

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 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.

[15] 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 band.

**Table 2:** 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 |
| 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 1 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. 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 an indicator for pixels with public parks and roads. 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.

## 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 $\beta_I < \beta_{II} < \beta_{III}$.

Critically, we find a monotonic pattern consistent with selection bias, but it disappears once we include our granular fixed effects. In Table 3, 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

**Table 3:** 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 ($H_0 : \|\beta_I\| \leq \|\beta_{II}\|$) | 0.06 | 0.90 | 0.39 | 0.12 | 0.33 | 0.45 |
| p-val ($H_0 : \|\beta_{II}\| \leq \|\beta_{III}\|$) | 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 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.

statistical power for this test with the BDD sample, as there are not enough boundaries to separately identify an effect for each wave. In columns 4 through 6, we reach similar conclusions for building heights: there is a slight monotonic pattern but it 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. For each pixel, we code the presence of KIP investments (paved roads, sanitation facilities, and public buildings) within 500 meters, from our policy maps. Reassuringly, once we include our fixed effects, neither the distance nor the investments controls materially change the estimates of our coefficients of interest.

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, 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. Several aspects can contribute to delayed formalization: upgraded slums could be less likely to be redeveloped because they are more crowded, because they have higher neighborhood quality, or because of more established perceived ownership rights by residents. Below, we consider household density and amenities.

## 6.1 Informality

We measure informality by the appearance of the neighborhood on photos and the legal status of land parcels. Figure A6 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 4 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.

**Table 4:** Effect of KIP on informality

| Dependent variable: | **Rank-based index** | | | **Unregistered parcels (shares)** | | |
|---|---|---|---|---|---|---|
| Sample: | Full Sample (1) | Historical Kampung (2) | BDD 200m (3) | Full Sample (4) | Historical Kampung (5) | BDD 200m (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 1, 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 exacerbate ownership disputes and holdout problems. Columns 1 through 3 of Table 5 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 log length of roads in the pixel, as the presence of road intersections may mechanically increase observed land fragmentation.

In a similar vein, columns 4 through 6 show that household density in KIP is higher. Applying the 0.41 coefficient 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.[16] Our data is not

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

**Table 5:** 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 1, 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.

granular enough to decompose these effects in a definitive way, but we find no evidence of differential in-migration, fertility, or mortality, 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 suggestive tests in Section 8.2.

## 6.3 Amenities

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

**Initial KIP investments.** The physical upgrades can have persistent impacts on land values through the direct effects of durable investments or by encouraging private investments. Table 6 investigates heterogeneity by the intensity and type of 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 investments located within a 500 meter buffer as total length of vehicular and pedestrian KIP-provided roads and number of sanitation facilities and public buildings. We do so for observations in KIP and non-KIP areas, allowing for the possi-

households per pixel, inclusive of 14.

**Table 6:** 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.

bility that residents in non-KIP areas were also able to access these 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.** Next, we consider current amenities of two types. 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 A4 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.

Taken together, KIP neighborhoods today are more informal, with more fragmented land, and greater density. These patterns are consistent with KIP being attractive to informal residents through strengthened perceptions of tenure security and greater land assembly costs deterring redevelopment. The land value effects are not associated with differences in physical KIP upgrades and access to modern amenities in non-KIP places also appears comparable by now.

# 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. What are the sources of societal gains in a counterfactual without KIP, 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 (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 a discussion of caveats and extensions.

## 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 ($i$), where to work ($j$), and how much housing to consume. The indirect utility of individual $\omega$ of type $g$ living in $i$ and working in $j$ is:

$$U^g_{ij\omega} = (u^g_i)^{\rho^g} Y^g_{ij} (r^g_i)^{(\beta^g-1)} \varepsilon^g_{i\omega} \upsilon^g_{j\omega} \tag{2}$$

which 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 $Y^g_{ij}(r^g_i)^{(\beta^g-1)}$, where $r^g_i$ denotes housing rents per square meter of built-up space and (1-$\beta^g$) is the budget share spent on housing. Resident $\omega$'s income $Y^g_{ij}$ includes a workplace-specific wage $w^g_j$ that is discounted by commuting costs $d_{ij}$. The two idiosyncratic taste shocks, for residence ($\upsilon^g_i$) and workplace ($\varepsilon^g_j$), are drawn independently and sequentially from a Fréchet distribution with shape parameter $\theta > 1$. This is robust to assuming simultaneous draws (Tsivanidis, forthcoming).

Locations are differentiated by amenities and rents. The term $u^g_i$ is a bundle of local amenities, with $\rho^g$ governing type-$g$ preference weight. It includes an exogenous component $\overline{u}^g_i$ and an endogenous one that depends on the share of type-$H$ residents: $u^g_i = \overline{u}^g_i \cdot (Sh^H_i)^{\mu^g}$. Exogenous amenities $\overline{u}^L_i$ include basic public goods and tenure security, which are plausibly higher in KIP locations, whereas $\overline{u}^H_i$ may include public space and landscape amenities. Both types benefit from $(Sh^H_i)^{\mu^g}$, 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 ($\mu^H > \mu^L > 0$).

Solving the residents' problem by backward induction, the share of group $g$ residents choosing to live in $i$ is:

$$p^g_i = \frac{(\Phi^g_i)^\theta}{\sum_i (\Phi^g_i)^\theta} \tag{3}$$

where $\Phi^g_i \equiv (u^g_i)^{\rho^g} (\overline{Y}^g_i)(r^g_i)^{(\beta_g-1)}$. The term $\overline{Y}^g_i$ denotes the expected income of location $i$ residents given their optimal workplace choice. It is a function of the wages paid by jobs accessible from location $i$, as summarized by residential commuter market access ($RCMA_i$) (Tsivanidis, forthcoming). 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:

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

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.[17]

## 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 $h_i^g$.[18]

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).[19] 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 $\phi^g$ of each plot is buildable, with $\phi^H \leq \phi^L$ 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 $\tau_i$, reflecting land market frictions. Additionally, each plot is subject to idiosyncratic profits shocks $(\zeta_H, \zeta_L)$ for each type of land use,

[17] 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.

[18] 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.

[19] 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).

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). Land rents are redistributed equally to all residents within each group through lump-sum payment $\bar{r}^g$.[20] This ensures that all the gains (producer and consumer surplus) are included 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 location choice optimization (3):

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

(ii) **Land Use:** The share of land 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:

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

[20]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 seven locations in total. We address robustness to the choice of spatial units in Section 7.6. Below, we outline the main data preparation steps, our approach to construct KIP counterparts, and key model parameters and assumptions. 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 ($\lambda_i^g$) 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 $\lambda_i^L$ accordingly. Similarly, we classify land values and heights observations to $H$ or $L$ based on parcel density. 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 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 in each region.

**Constructing KIP counterparts.** We construct KIP counterparts to match the reduced-form KIP effects for the center/middle/peripheral regions. 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. We interpret the KIP estimates as reflecting direct KIP effects on the own-region, without allowing for indirect effects such as sorting and spillovers involving the broader economy. 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 $\left(L_{i'}^g, \lambda_{i'}^g, h_{i'}^g, r_{i'}^g\right)$ for $i' = (Center, KIP)$ 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 log land values (column 1) and log heights (column 3) estimated in Table 2 for the

Center.

**Model-implied wedges.** Through the lens of the model, wedges in land values and building heights between KIP and non-KIP locations arise from differences in amenities ($\overline{u_i}^g$) and formalization costs ($\tau_i$). From the non-KIP data and the equilibrium conditions, we can infer how large the model-implied wedges in amenities and formalization costs have to be to rationalize the estimated KIP wedges in land values and heights. Following Ahlfeldt et al. (2015), amenities are identified (up to a group-specific constant) from the location choice condition, leveraging population and rents. We recover $H$ ($L$)-type amenities to be high in locations we observe a high $H$ ($L$)-type population density relative to local formal (informal) rents. We normalize amenities in the outermost region as 1. Formalization costs $\tau_i$ are pinned down by relative formal and informal profits and land shares, rearranging equation (7). We discuss the recovered values for $\overline{u_i}^g$ and $\tau_i$ in Table B.1 in the Appendix.

**Parameters.** Table 7 describes the parameters. We set the commuting elasticity to $\theta = 3$ (Tsivanidis, forthcoming). We match housing budget shares to those in the SUSENAS household survey for Indonesia. The values are comparable to other developing countries (Balboni et al., 2020). At baseline, we set the amenity spillover parameter $\mu^H = 0.88$ (Gechter and Tsivanidis, 2023)'s estimates for Mumbai and $\mu^L = 0.3\mu^L$ in line with the gentrification literature (e.g. Diamond (2016), Su (2022).) We discuss robustness to these parameters in Section 7.6 and Table B.2. We set the amenity multiplier $\rho_L = 1$ to normalize and $\rho^H = 1.034$ (Gechter and Tsivanidis, 2023). Our results are robust to setting both to 1.

On the supply side, we set the cost elasticity with respect to heights as $\nu = 1.69$ (Sturm et al., 2023), which implies a housing supply elasticity of $\frac{1}{(\nu-1)} = 1.45$. This closely aligns with Henderson et al. (2020) for Nairobi and is in the ballpark of other estimates (e.g. Saiz (2010), Heblich et al. (2020)). For built-up coverage shares, we set $\phi^H = 0.3$ throughout the city and $\phi^L = 0.5$ (center and middle) and 0.3 (periphery). The values are consistent with Henderson et al. (2020) and our data. Our conclusions remain if $\phi_i^L$ is constant. The profit shock dispersion $\gamma$ governs how sensitive the land use choice is to relative profits, under a functional form assumption similar to Gechter and Tsivanidis (2023). We estimate it using the cross-elasticity of informal land shares to formal rents, from regression estimates with fixed effects and controls (see Section B.2.2). We recover $\gamma = 1.18$. Additional details and robustness are discussed in the Appendix.

**Data calibration**. We calibrate several parameters to match Indonesian/Jakarta moments. We set informal building costs $\bar{c}^L$ at 200,000 Rupiahs (USD 12) per square meters from industry reports (Nurdini et al., 2017), but our results are robust to considering alternative values (see Section B.2.2 in the Appendix) and to assuming elastic heights in the informal sector, which does not rely on this value. We recover model-implied wages $w_i^g$ from population and employment using a commuting survey for Jakarta (Gaduh et al., 2022).

**Table 7:** List of parameters, estimation methods, and sources

| Parameter | Description | Value | Source |
|---|---|---|---|
| $\theta$ | Commuting elasticity | 3 | Tsivanidis (forthcoming) |
| $\beta^H$ | Housing budget shares | 0.17 | SUSENAS household survey |
| $\beta^L$ | | 0.13 | (Badan Pusat Statistik, 2008) |
| $\mu^H$ | Amenity spillovers | 0.88 | Gechter and Tsivanidis (2023) |
| $\mu^L/\mu^H$ | | 0.30 | Diamond (2016) |
| $\rho^H$ | Amenity multiplier | 1.03 | |
| $\rho^L$ | | 1 | Gechter and Tsivanidis (2023) |
| $\frac{1}{(\upsilon-1)}$ | Floorspace supply elasticity | 1.45 | Sturm et al. (2023) |
| $\phi^H$ | Built-up coverage shares | 0.3 | |
| $\phi^L$ | | 0.5 (0.3 in Periphery) | Henderson et al. (2020) |
| $\gamma$ | Profit shock dispersion | 1.18 | Estimated from cross-elasticities of land shares to rents. |

## 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.

### 7.5.1 Effects of lifting KIP everywhere

As a benchmark, we begin by considering a counterfactual where we lift KIP everywhere in the city. This amounts to setting $(\overline{u}_i{}^g, \tau_i)$ in each KIP region to match the values in the corresponding non-KIP region. We present the results in Table 8, Panel A. 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 gain 5.2% and $L$ types lose 2.1%, with the city as a whole experiencing welfare gains of 3.3% and a 2.5% 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. Our finding of city-wide gains associated with formalization also echo those in Henderson et al. (2020) for Nairobi.

Next, we assess the role of direct versus general equilibrium effects in explaining the welfare result. Considering direct effects, as KIP is lifted, the formal land share increases, formal rents fall and informal rents increase, benefiting $H$ types and harming $L$ types. Additionally, $L$ types are displaced away from KIP regions to lower-amenity locations. Lifting KIP also entails reducing the

**Table 8:** Effects of lifting KIP

| | H | L | All |
|---|---|---|---|
| **Panel A: City-wide** | | | |
| Welfare % | 5.2% | -2.1% | 3.3% |
| Population % | 5.6% | -5.3% | 2.5% |
| | | | |
| **Panel B: By Region** | | | |
| Welfare % | | | |
| Center | 4.3% | -2.3% | 2.6% |
| Middle | 0.7% | -0.3% | 0.4% |
| Periphery | 0.1% | 0.2% | 0.1% |

$L$-type exogenous amenities and enhancing $H$-type amenities, which exacerbates the effects above. We find that the direct welfare impacts of lifting KIP are 4.5% for the $H$ types and $-3\%$ 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 as a result end up facing different rents and employment income; 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.

### 7.5.2 Where to formalize

In Panel B of Table 8 we show that 78% 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. In the Center, the gains for the $H$ types are the largest (4.3%) but so are the losses for the $L$ types (-2.3%). On net, the city-wide effects from lifting KIP in the center (2.6%) are 78% of the effects from lifting KIP in the entire city. The key source of misallocation associated with KIP today is that the program is prevalent precisely in this part of the city.

The finding of greater formal gains and informal losses from lifting KIP in the center lines up with the monotonic pattern of larger reduced-form KIP estimates for the center, followed by the middle, then the periphery (see Table 2). In the model, the Center is where the wedge between formal and informal profits is the largest, resulting in larger gains from formalization. This is also where the $H$ types receive the largest amenity boost from lifting KIP and the $L$ types suffer the largest amenity drop. To corroborate this, 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.[21] Outside of the center, we find small city-wide effects from lifting KIP (0.4% and 0.1% 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.

#### 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 9 we consider counterfactuals where we lift KIP from a smaller portion of the city and consider ways to minimize losses for low-income residents. In this context, lifting the KIP bundle can be thought of as the government easing restrictions to redevelopment associated with KIP, mediating with developers to facilitate land assembly. We provide 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 (-0.05%). If this is bundled with a zoning policy allowing for taller formal buildings (which we implement in the model by boosting $\nu$ by 25% or 35%), the $L$-type losses are reversed (0.01% 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 the implementation of these transfers difficult in practice.

### 7.6 Robustness

**Model parameters.** We perform several sensitivity and robustness exercises. In Table B.2 we present the welfare gains from lifting KIP everywhere under different assumptions concerning

[21] 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.

**Table 9:** Balancing equity and efficiency

| | H | L | All |
|---|---|---|---|
| Lift KIP | 1.31% | -0.05% | 0.94% |
| Lift KIP + zoning height boost ($\Delta u$ = 25%) | 1.48% | 0.01% | 1.08% |
| Lift KIP + zoning height boost ($\Delta u$ = 35%) | 1.55% | 0.03% | 1.13% |
| Lift KIP + zoning height boost ($\Delta u$ = 50%) | 1.80% | 0.11% | 1.33% |
| Lift KIP + redistribute 5% H rents | 1.11% | 0.26% | 0.87% |
| Lift KIP + redistribute 10% H rents | 0.90% | 0.58% | 0.81% |

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.

**Variation from heights only.** 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 (3.5% 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. Our key patterns of larger gains in the center are preserved and we also continue to find that the majority of the gains are driven by direct effects.

## 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. Below we discuss a number of caveats to our model.

First, our model does not feature a production sector where firms use land for commercial purposes. Second, our model assumes segmented housing markets and does not allow the $L$ types to consume $H$-type housing. Relaxing this assumption would allow some of the $L$-types to share the formal gains by upgrading to formal housing and would plausibly lead to lower welfare losses for the $L$ types. One way in which our model approximates these effects is in our counterfactual exercise where we share some of the formal land surplus with the $L$ types. Future research could consider intergenerational effects on slum residents who become formal. To the extent that formalization continues to benefit the $H$ types more in the center, our welfare conclusions would continue to hold in a richer model.

Finally, the model is static and our efficiency claims may not carry through to a dynamic setting. As long as 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, for example as a result of natural disasters (e.g. flooding). 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, which we cannot do without historical data on displaced residents.

# 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 6). 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.

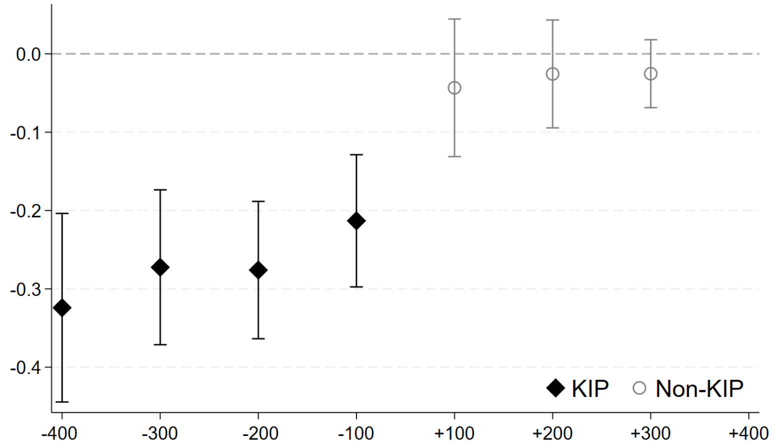
**Spatial decay on both sides of KIP boundaries.** Figure 3 investigates the extent of spillovers by analyzing patterns of spatial decay, under the premise that localized exposure effects should decline with distance (Turner et al., 2014, Anagol et al., forthcoming). We focus on distance bands of up to 500 meters.[22] 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.

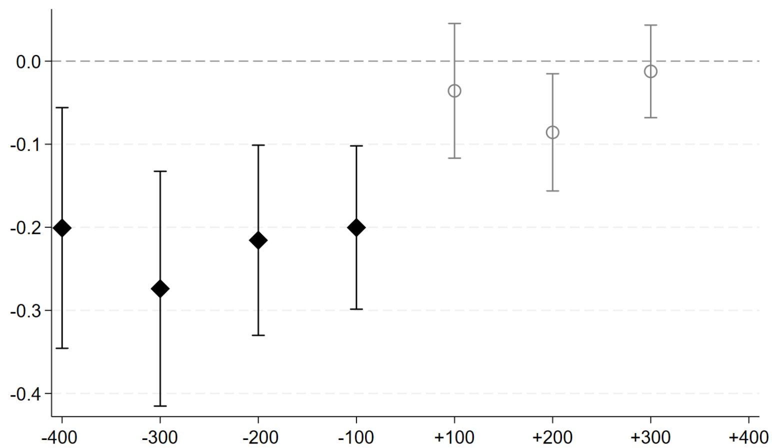
**BDD robustness.** In line with the spatial patterns above, Table A5 shows that our BDD estimates are similar if we consider alternative buffer distances (the optimal bandwidth as per Calonico et al.

[22] 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).

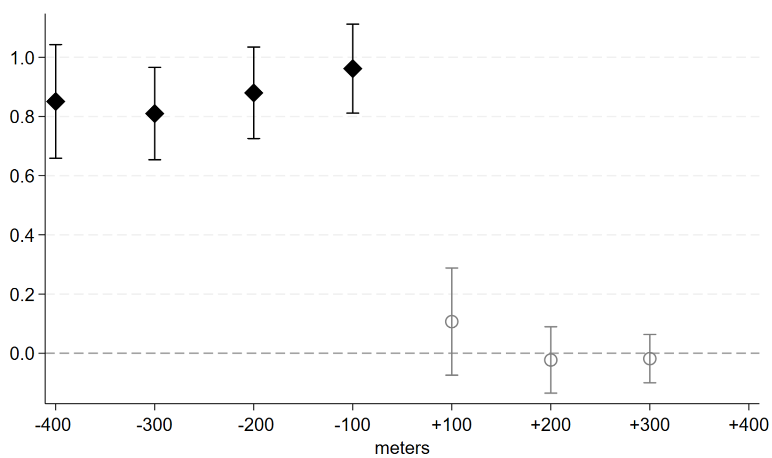
**Figure 3:** Spatial decay: distance from KIP boundaries




**(a)** Log land values




**(b)** Log building heights




**(c)** Log parcel density

Notes: We employ a similar specification as our BDD analysis in Table 1, but replace distance to the KIP boundary with dummies for 100m-wide distance bins, pooling the two outermost bins for 400m and 500m.

(2014) and 500 meters). Table A6 shows that our BDD estimates are also robust to excluding boundaries that overlap with historical and contemporaneous waterways and roadways.

## 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 $\varepsilon_{ijt}$ 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 comparing 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 ($\delta_j$) 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 10 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

**Table 10:** 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.

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 lower ($-0.13$) in historically denser places (column 2). The KIP effects on land values and heights, however, remain stable with or without controlling for historical density, suggesting the potential bias from historical density is muted.

**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 (Table A10), which tends to go against the lower land values in KIP. These results 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 and land values.** 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 A11 shows that the results for building heights survive after dropping pixels with parks and large roads (columns 1 through 3) or restricting to pixels within 1000 meters of pre-determined historical main roads, as a proxy of market access (columns 4 through 6).

Table A12 considers selection into our land values dataset by KIP status, showing that KIP areas are not underrepresented. If anything, KIP pixels in the full sample are 3% more likely to have an assessed land value observation. In the historical sample the percentage is 4%.

**Standard errors robustness.** We replicate the specifications in Table 1 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 1969-1984 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 78% of the welfare gains from removing KIP are 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 for the beneficiaries of slum upgrading programs.

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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 |
| 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, km | 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). 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.

## **Table A2:** 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.

Table A2 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).

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.

## Other building height outcomes

Table A3 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 point estimates ranging from -0.09 to -0.19.

**Table A3:** 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*** | -0.47 | -0.09*** | -0.19*** | -0.17** |
| | ( 0.31) | ( 0.37) | ( 0.70) | ( 0.03) | ( 0.04) | ( 0.07) |
| N | 19515 | 5277 | 4128 | 17233 | 5061 | 3923 |
| R-Squared | 0.39 | 0.32 | 0.52 | 0.41 | 0.37 | 0.62 |
| 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 1 for the height dummy. Standard errors are clustered by locality, except for the BDD where we cluster by KIP boundary.

## Current amenities

Table A4 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 in 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 36% 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 A4:** 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 88,832 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 A5 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 16% 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).

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 A5:** Boundary analysis, robustness to different bandwidths

| Dependent variable: | **Log land values** | | **1(Height>3)** | |
|---|---|---|---|---|
| | BDD | BDD | BDD | BDD |
| | 500m | Optimal | 500m | Optimal |
| | (1) | (2) | (3) | (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 1. 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 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 1. 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 persistently lower land values today, (-0.13) but limited influence on the KIP coefficient, which remains stable around -0.34 with or without controlling for historical density. Since historical density is defined at the locality level, in columns 1 and 2 we can only include fixed effects at the sub-district level (larger than localities). In column 3, we show that with our baseline specification (with controls and hamlet fixed effects) we can recover a -0.9 effect. This is slightly different from the -0.11 point estimate of the the full sample specification in Table 1, because we lost 4307 observations which cannot be matched with historical density. For heights (columns 4 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. In addition to 1960, we collected 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 one standard deviation increase in the share of KIP (0.28) is associated with a 0.33 increase in log 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: | **Log density** | **Change in log density** |
|---|---|---|
| | (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 1, 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. We find similar results when restricting the sample to stayers only (defined based on the district of birth coinciding with the current district).

**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.

## Other robustness checks: Selection bias for building heights

Below, we consider selection bias in the heights results stemming from the fact that the potential for building high-rises depends on zoning regulations and market access. In Table A11, we show that the results for building heights are similar if we drop pixels with parks and large roads (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 A11:** 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 parks/large roads 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 1. 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 A12 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.

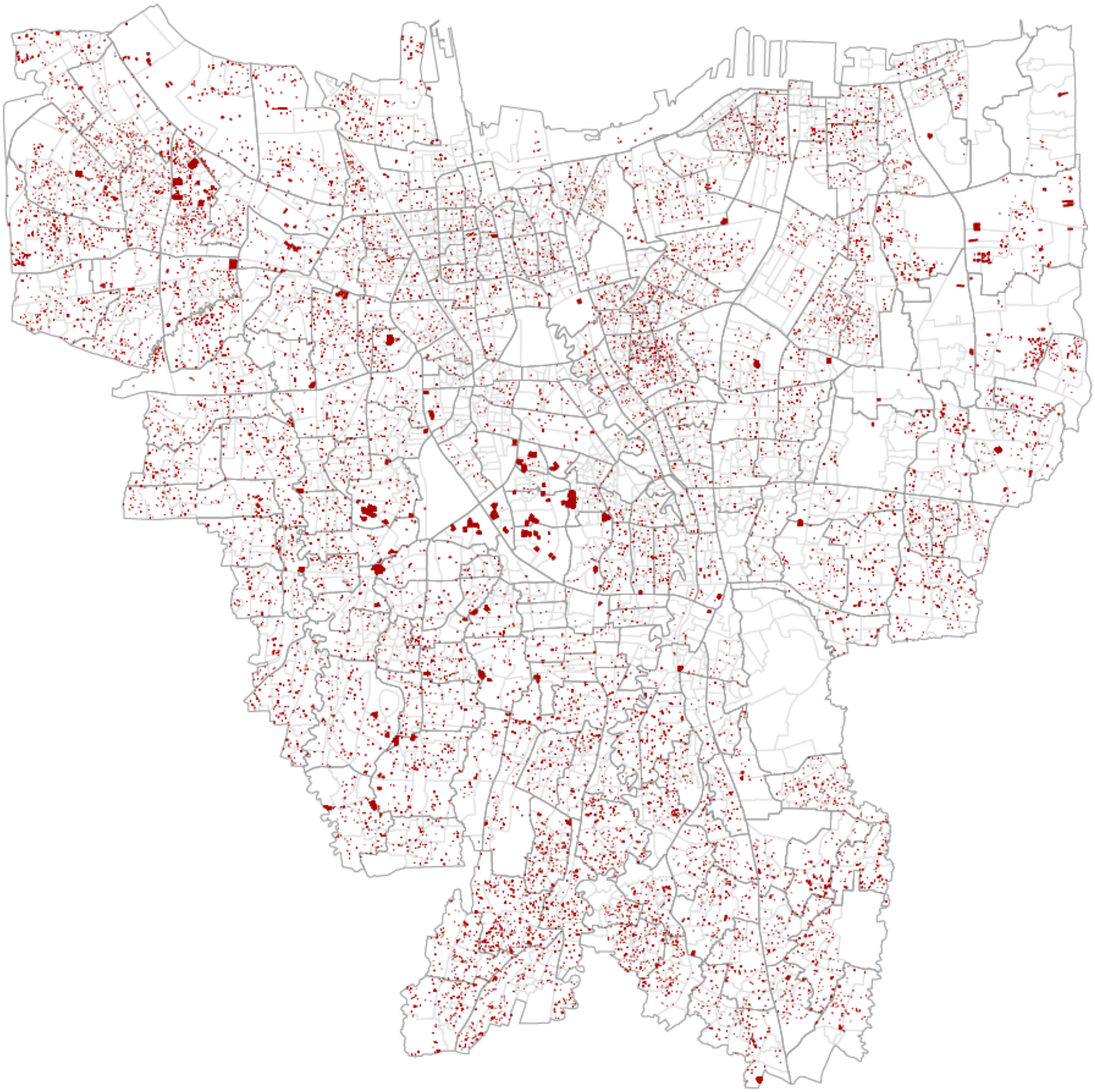
**Table A12:** Selection for assessed land values

| 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:** Scatterplot of assessed land values and transaction prices

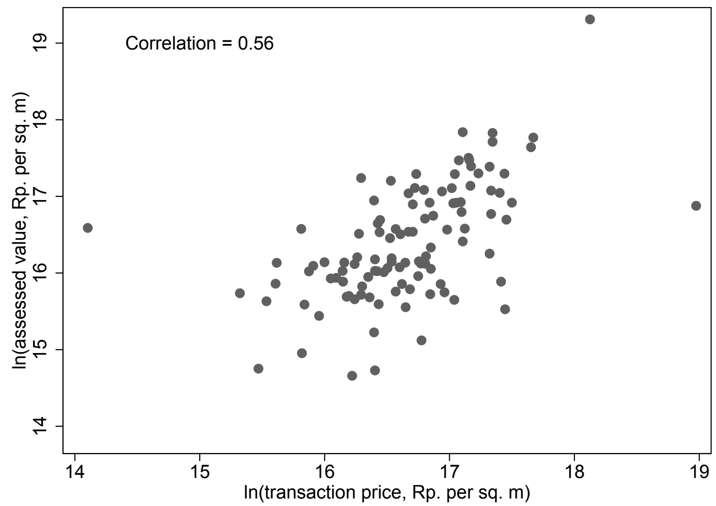
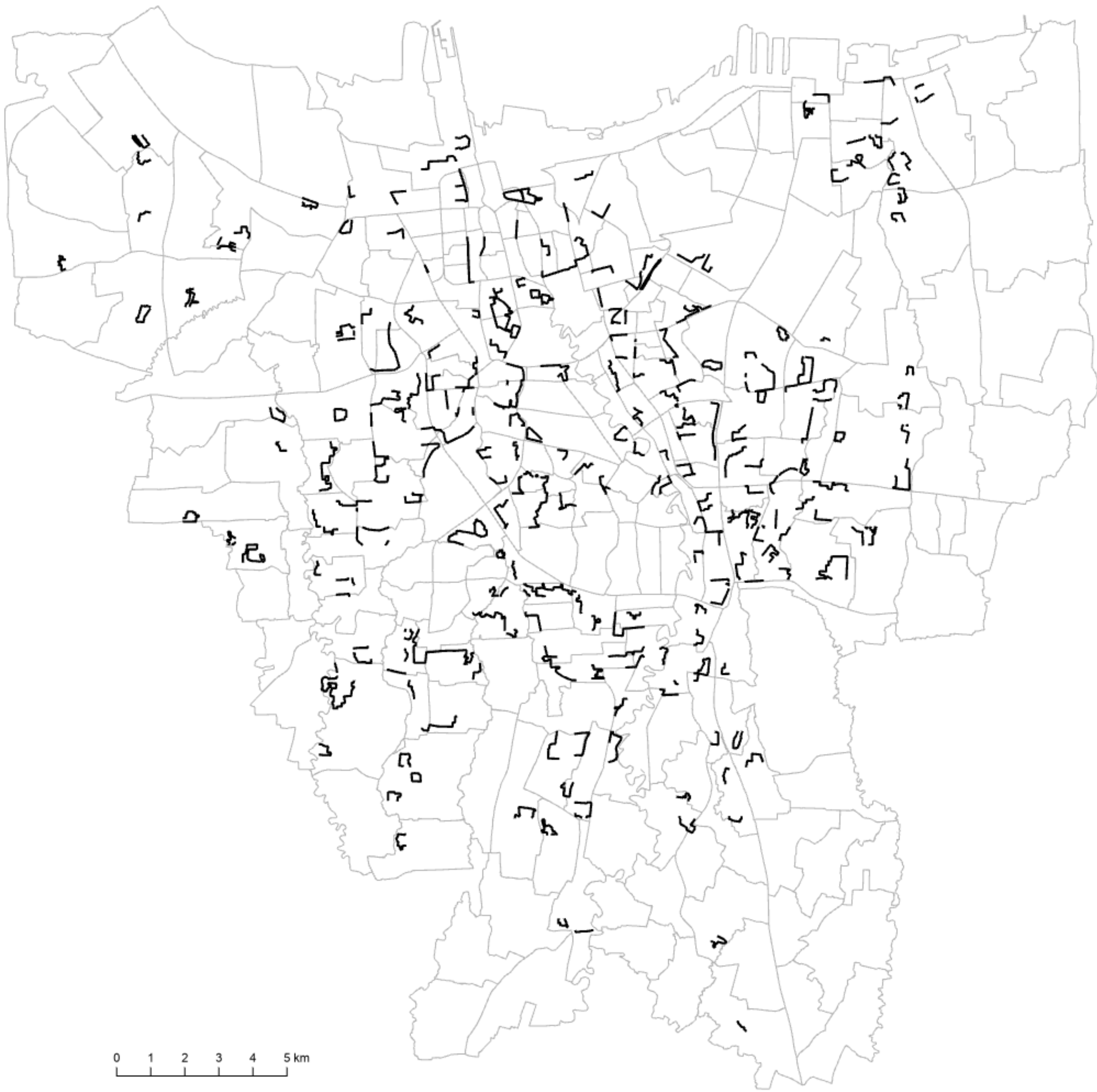



Figure A2 shows the correlation between the log of assessed land values and the log of property transactions prices. Each point represents values per square meter, averaged at the hamlet level, from Indonesia's largest property website. Our main results for land values remain similar after dropping hamlets corresponding to the 3 outliers visible in the plot (two on the right and one the left).

The correlation is 0.56. This 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, as 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.

**Figure A3:** Examples of coding of the rank-based informality index

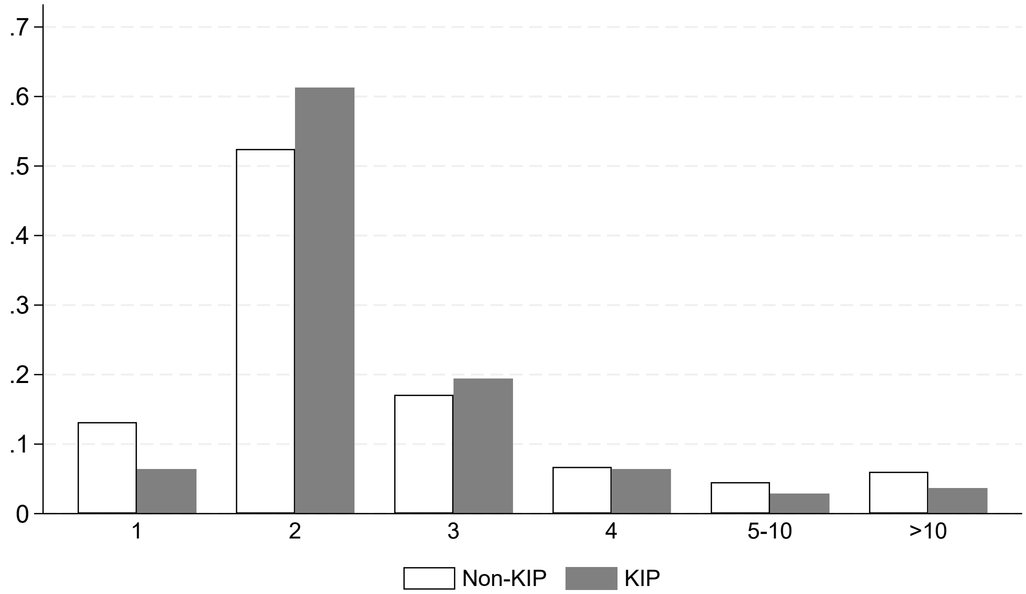
**Figure A4:** Map of KIP boundary segments




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.

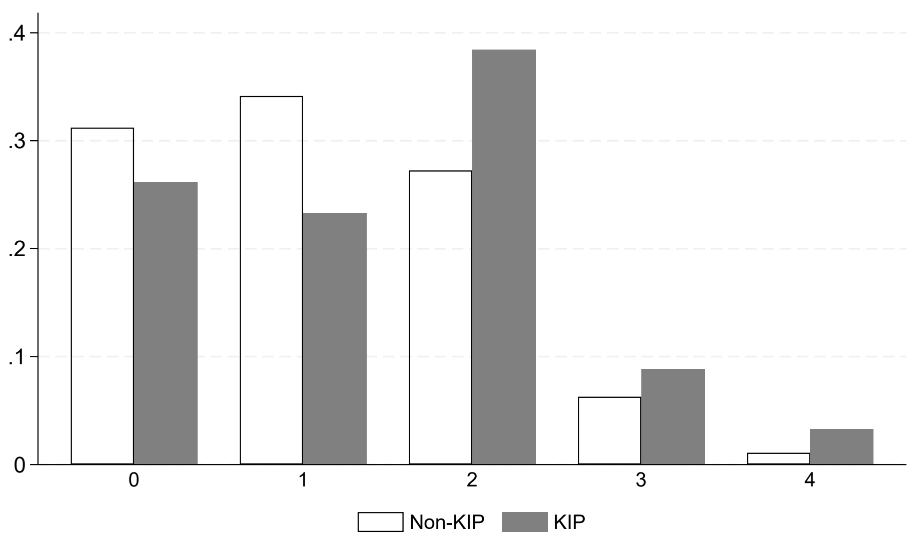
Figure A5 shows that non-KIP locations have more tall buildings (white bars at the right tail). We plot the distributions of building heights by KIP status in the photographic sample. KIP pixels (grey bars) are more likely to have shorter buildings whilst non-KIP pixels (white bars) are more likely to have taller buildings.

**Figure A5:** Building heights in KIP and non-KIP



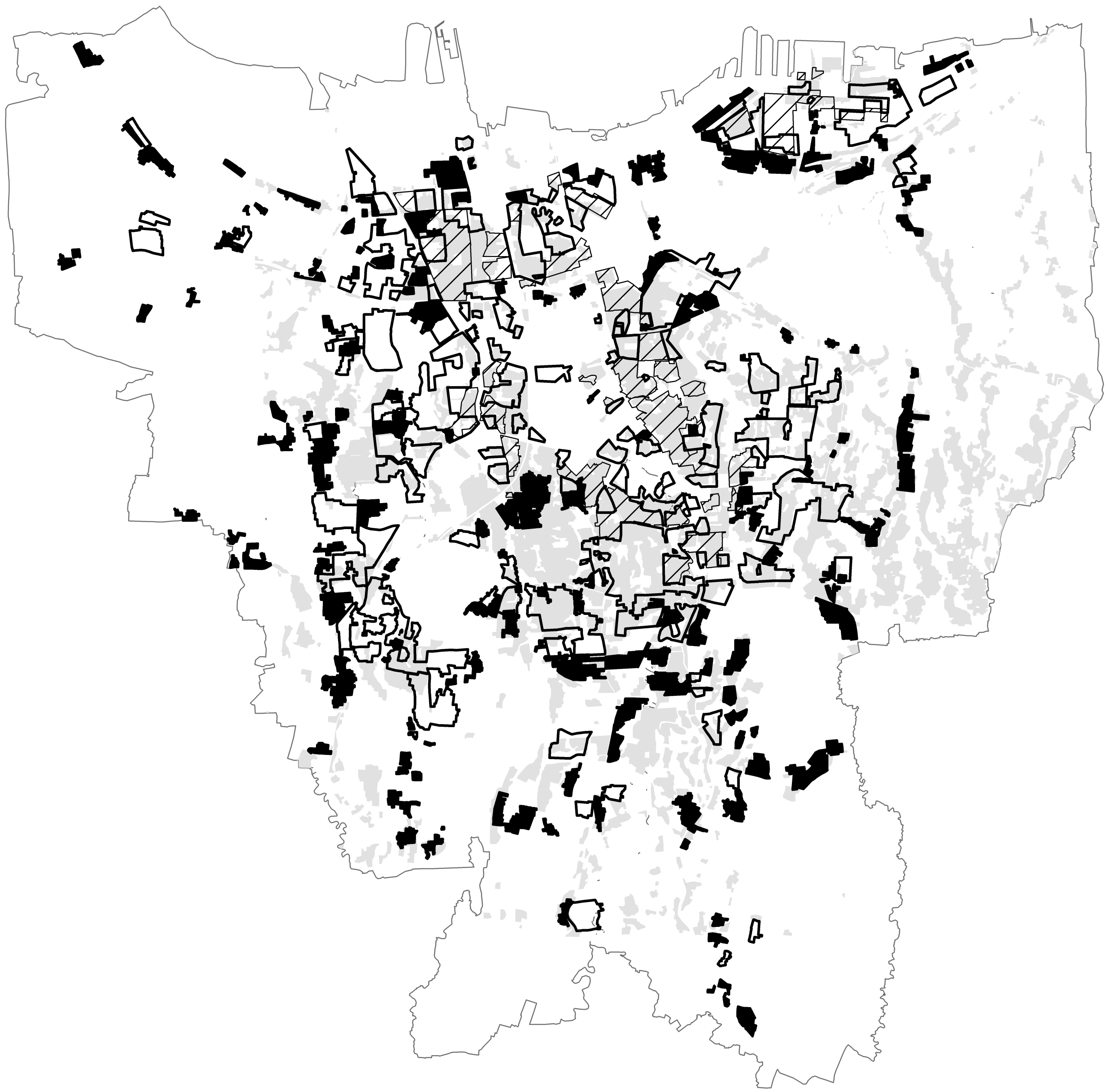

Notes: This bar chart shows the distribution of building heights for the tallest building in KIP and non-KIP pixels in the photographic sample. KIP and non-KIP pixels correspond to grey and white bars, respectively. The horizontal axis represents the number of floors. The vertical axis reports the share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

**Figure A6:** Rank-based informality index in KIP and non-KIP



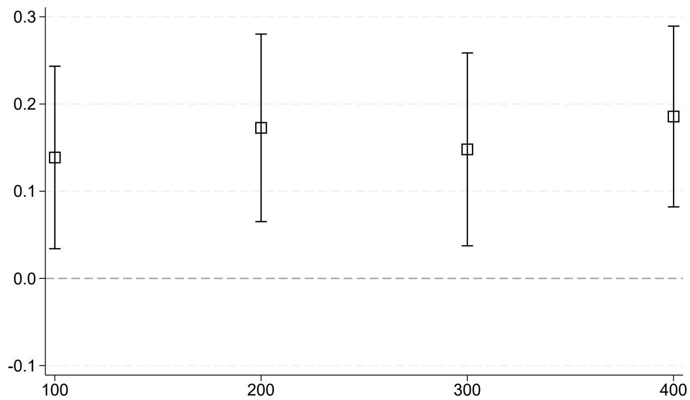

Notes: Distribution of the rank-based informality index by KIP status for the full sample of 19,515 pixels. Index values range from 0, corresponding to "very formal", to 4, corresponding to "very informal". The gray and white bars correspond to KIP and non-KIP pixels, respectively. The vertical axis indicates the share of the pixels by KIP status with each of the two groups (summing to 1). For the sub-sample of 7,101 pixels that were ranked by two research assistants, we assign a weight of 0.5 to each score.

**Figure A7:** Map of KIP waves

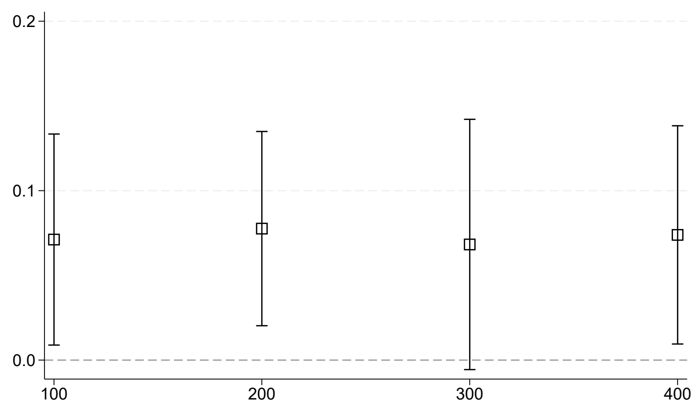


Notes: Map showing areas treated as part of the 3 KIP *Pelita* waves. Striped, hollow, and black areas were respectively exposed to KIP wave I, II, and III. Historical slums are shown in grey.

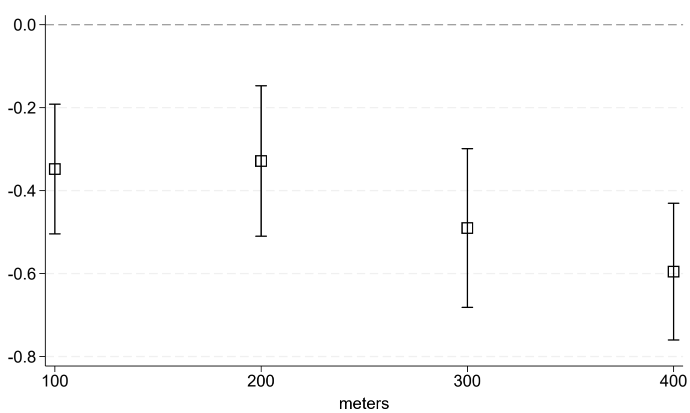
**Figure A8:** Spatial decay: Distance from non-KIP slums




**(a)** Log land values




**(b)** Log height




**(c)** Log parcel density

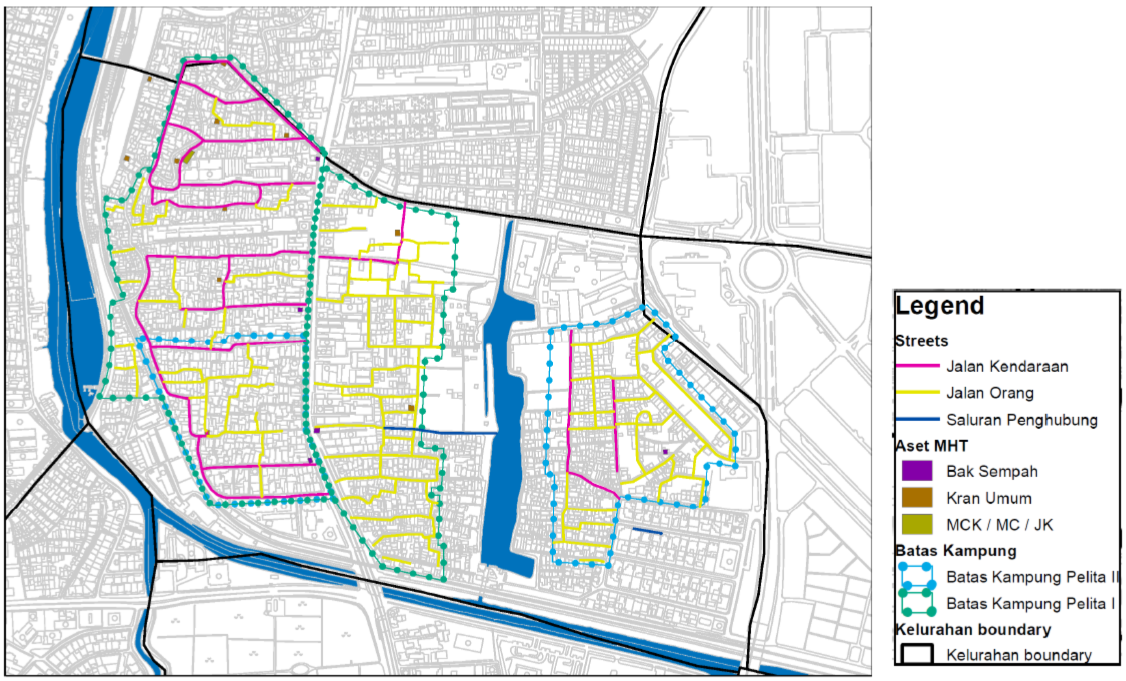
Notes: We investigate the spatial decay pattern of land values away from the boundaries of 45 high-density, informal, and non-KIP hamlets. Specifically, these hamlets do not belong to KIP, have population density above the median, and appear as kampungs as per our photo survey (rank-based index values 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 1, 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 explored robustness to 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 A4 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 A2, 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.

**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. For a subsample of 7,101 pixels, two rankings were independently produced by two research assistants. 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.

## Land titles

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

## Control variables

At baseline we include eight landmark controls, capturing the distance, in logs, from a number of historical landmarks predating KIP. We consider the 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. Additionally, we include log distances from the coast and from the nearest permanent or semi-

**Figure A10:** Example of cadastral map of land parcels

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

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 small number of control variables (flow accumulation, distance to the Concert Hall), resulting 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 A13:** 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 $\omega$ 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 $\theta$. As shown in Tsivanidis (forthcoming), the alternative assumption of a simultaneous choice of the pair $(i, j)$ yields very similar equations. We set $\theta = 3$ from Tsivanidis (forthcoming).[23]
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). 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 (forthcoming) 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 $(\Phi^g_{j|i})^\theta$ and shape $\theta$, where

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

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

$$p^g_{j|i} = \frac{(\Phi^g_{j|i})^\theta}{\sum_j (\Phi^g_{j|i})^\theta}. \tag{B.4}$$

[23] We assume $\theta$ is the same for both groups and draws. An earlier version of Tsivanidis (forthcoming) 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 $\theta$ to vary by group and draw using those parameter values.

Following Tsivanidis (forthcoming), we define residential market access in neighborhood $i$ as $RCMA_i^g \equiv \sum_j \left(\frac{w_j^g}{d_{ij}}\right)^{\theta}$. Equation B.4 can be rearranged as

$$p_{j|i}^g = \frac{\left(w_j^g/d_{ij}\right)^{\theta}}{\text{RCMA}_i^g}. \tag{B.5}$$

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

$$\overline{w}_i^g = \sum_j p_{j|i}^g \cdot \mathbb{E}\left(\frac{w_j^g}{d_{ij}}\middle| j \text{ was chosen}\right).$$

By Fréchet properties,

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

with $\widetilde{\Gamma} = \Gamma\left(\frac{\theta-1}{\theta}\right)$, which yields $\overline{w}_i^g = \widetilde{\Gamma}\,\text{RCMA}_i^{\frac{1}{\theta}}$. 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 $\overline{Y}_i^g = \overline{w}_i^g + \overline{r}^g$.

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

$$U_i^g = (u_i^g)^{\rho^g} (\overline{Y}_i^g) \left(r_i^g\right)^{\beta^g - 1} \varepsilon_i. \tag{B.6}$$

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

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

and the share of group $g$ residents residing in $i$ is

$$p_i^g = \frac{\left[(u_i^g)^{\rho^g} (\overline{Y}_i^g) \left(r_i^g\right)^{\beta^g - 1}\right]^{\theta}}{\sum_i \left[(u_i^g)^{\rho^g} (\overline{Y}_i^g) \left(r_i^g\right)^{\beta^g - 1}\right]^{\theta}}.$$

**Open city** The total measure of residents in Jakarta is pinned down by the mobility condition on p. 24. 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:

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

We consider Jabodetabek (greater Jakarta) as the broader economy, setting the total population to $\overline{L}_{econ}^H + \overline{L}_{econ}^L = 9.8$ 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 $(\lambda_i^g)$, rents $(r_i^g)$, and population, $(L_i^g)$ 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 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 $\lambda_i^L$. 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 $Shr^g$:

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

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 $Shr^g$ 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** 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. 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%. We impute population density by region and KIP status by intersecting block maps and KIP policy polygons. We exclude areas with low population density.

### B.2.2 Model parameters and data calibration

Below we discuss our key parameters and robustness. We estimate $\gamma$, the profit shock dispersion parameter. We take other parameters from the literature or to match Indonesian data.

**Amenity parameters** Following Gechter and Tsivanidis (2023), we normalize $\rho^L = 1$ and set $\rho^H = 1.034$. Our results are robust to setting both to 1, removing the extra utility boost that $H$ types get. 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).

**Model-implied wages and Residential Commuter Market Access** We follow the procedure in Tsivanidis (forthcoming) to estimate $\overline{w}_i^g$ from employment and population counts.

Define Firm Commuter Marke Access $FCMA_j^g \equiv \sum_i \left(\frac{u_i^g (r_i^g)^{\beta g-1}}{d_{ij}}\right)^{\theta}$. This captures access to workers from workplace location $j$. Denote employment in $j$ as $L_{Fj}^g \equiv \sum_i p_{j|i} \cdot L_i^g$. This can be rewritten as $L_{Fj}^g = \sum_i \frac{\left(w_j^g / d_{ij}\right)^{\theta}}{\text{RCMA}_i^g}$. Tsivanidis (forthcoming) shows that $RCMA_i^g$ and $FMCA_j^g$ are linked through the following system of equations:

$$\begin{cases} \text{RCMA}_i^g & = \sum_j \frac{L_{Fj}^g}{d_{ij}^{\theta}} \cdot \frac{1}{\text{FCMA}_j^g} \\ \text{FCMA}_j^g & = \sum_i \frac{L_i^g}{d_{ij}^{\theta}} \cdot \frac{1}{\text{RCMA}_i^g}. \end{cases}$$

Using employment ($L_{Fj}^g$) and population ($L_i^g$) counts, the system of equations above can be solved for $\text{RCMA}_i^g$, up to a group-specific constant.

We implement this calculation with additional employment data from the 2010 Japan International Cooperation Agency (JICA) commuter travel survey (Gaduh et al., 2022)[24], 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, and subsequently choose in which locality to work and commute to (Kreindler and Miyauchi, 2023).

**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.[25]

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 $T_i^g$ to clear the floorspace markets (equation (11)).

Following Henderson et al. (2020), we set $\phi_i^H = 0.3$ in the formal sector, constant throughout the city; in the informal sector, we set $\phi_i^H = 0.5$ in the center and middle and 0.3 in the periphery. The values are consistent with our cadastral

[24] We thank Gaduh et al. (2022) for kindly sharing their code.

[25] 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.

maps data. Our conclusions are similar if we keep the informal coverage ratio constant at $0.5$ throughout the city.
For informal building costs, at baseline we consider 200,000 Rupiahs (USD 12) per square meters, but our results are robust to considering alternative values (125,000, 250,000, and 300,000). We benchmark $\bar{c}^L$ from industry reports (Nurdini et al., 2017) which indicate $5,000,000$ Rupiahs (USD 300) psqm one-time construction costs for kampung houses similar to those in Jakarta. We convert to a flow measure using a capitalization rate of $4.3\%$, obtaining $215,000$ Rupiahs psqm, rounded to $200,000$. For robustness we also consider benchmarking $\bar{c}^L$ from formal construction costs. ARCADIS (2019) reports median construction costs of USD 650 psqm for Jakarta. The difference between formal and informal elasticities in Henderson et al. (2020) implies informal costs equal to $30\%$ of formal ones, which yields $125,000$ Rupiahs. For our robustness exercise where we assume elastic informal supply, we use the same functional form as Sturm et al. (2023) and the informal elasticity estimated by Henderson et al. (2020). When we calibrate heights to rents we obtain average costs of $260,000$ Rupiahs psqm.

**Profit shock dispersion** There is no guidance in the literature on plausible values for the profit shock dispersion parameter $\gamma$, which governs the elasticity of land use shares to rents. 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 $\gamma > 1$. 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 $\lambda^H$, 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 $\gamma$ 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 $3.2\%$).

### B.2.3 Unobservables

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

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

We normalize amenities setting $u_{Outer}^g = 1$ where $Outer$ denotes the outermost (non-KIP) region in Jakarta.
We then retrieve the exogenous component $\overline{u}_i^g = u_i^g \left( \frac{L_I^H}{L_I^H + L_I^L} \right)^{-\mu^g}$.

**Formalization cost:** $\tau_i$ is pinned down by relative profits and land shares, rearranging (7):

$$\tau_i = 1 - \left( \frac{\lambda_i^H}{\lambda_i^L} \right)^{1/\gamma} \cdot \frac{\pi_i^L}{\pi_i^H}. \tag{B.11}$$

### B.2.4 Constructing model-generated KIP regions

Below we explain how we use our reduced-form estimates in Table 2 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. Through the lens of the model, wedges in land values and heights between KIP and non-KIP locations arise from differences in amenities and taxes. Our goal is to infer how large the wedges need to be to justify wedges in equilibrium land values and heights that match our reduced-form estimates.
Recall that we observe $(\lambda_i^g, r_i^g, h_i^g)$ for non-KIP locations (e.g. non-KIP, center) from the data. We implement a procedure to search for values of $(\lambda_i^g, r_i^g, h_i^g)$ in each corresponding KIP location (e.g. KIP, center) that deliver the wedges in land values and heights from Table 2. The steps are outlined below.

1. We anchor our procedure on the formal land share $\lambda_i^H$, which is bounded between 0 and 1. That is, we first pick a value of $\lambda_i^H$ and recover rents and heights to match the reduced-form moments.
   - Given $\lambda_i^H$, for each 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 2) and we get the third from the first-order condition for $H$-type housing supply. As an example, for the center, the estimates for log land values are -0.14 and the estimates for log heights are -0.13.
   - Given $\lambda_i^H$ and a fixed $h^L$, we can recover what $h^H$ has to be in KIP to imply an estimated KIP effect on log heights of 0.13 in the center.
   - Similar to Sturm et al. (2023), from the first-order condition for profit maximization, equation (10), there is a one-to-one mapping between rents and heights that allows us to infer rents.
   - Given $\lambda_i^H$ and $r_i^H$, we can recover $r_i^L$ in KIP such that the KIP effect on log land values is -0.14.
   - This way, we used 3 equations to recover 3 unknowns ($r_i^H$, $r_i^L$, 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 $\tau_i$ 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 (given rents, heights, and $\lambda_i^g$). Given population, we can recover amenities from location choice conditions (equation 9).

With the procedure outlined above, we recover a vector of rents, heights, population, amenities, and formalization costs for each $\lambda_i^H$, 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. We consider solutions where $\tau$ is higher than in non-KIP and select the one that minimizes the mean-squared error. This is our baseline KIP counterpart. 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.2.5 Model-implied wedges

**Table B.1:** Spatial distribution of model-implied wedges in amenities and taxes

| | | (1) | (2) | (3) |
|---|---|---|---|---|
| **Panel A:** | | $\overline{u}_i^H$ | $\overline{u}_i^L$ | $\tau_i$ |
| Center | Non KIP | 1.57 | 1.35 | 0.82 |
| | KIP | 1.45 | 1.69 | 0.83 |
| Middle | Non KIP | 1.20 | 1.17 | 0.16 |
| | KIP | 1.14 | 1.18 | 0.19 |
| Periphery | Non KIP | 1.06 | 0.90 | 0.41 |
| | KIP | 1.00 | 0.79 | 0.67 |
| **Panel B:** | | $\Delta\Phi_i^H$ | $\Delta\Phi_i^L$ | $\Delta\pi_i^{H/L}$ |
| Center | | 8% | -18% | 20% |
| Middle | | 4% | -2% | 3% |
| Periphery | | 3% | 8% | 1% |

Notes: Panel A reports exogenous amenity values for high and low types (columns 1 and 2) and the formalization tax rate, $\tau$ (column 3). Panel B reports percentage differences between non-KIP and KIP for each region. Columns 1 and 2 respectively report, for $H$ and $L$ types, the percentage differences for $\Phi_i^g \equiv (u_i^g)^{\rho^g}(\overline{Y}_i^g)(r_i^g)^{(\beta_g-1)}$. Column 3 reports percentage differences in the profit ratio, $\pi_i^{H/L} = \frac{(1-\tau_i)\pi_i^H}{(1-\tau_i)\pi_i^H+\pi_i^L}$.

Table B.1 reports the recovered $\overline{u}_i^g$ and $\tau_i$ across regions in Panel A and the corresponding percentage differences in KIP/non-KIP wedges in utility and profitability in Panel B. Columns 1 and 2 in Panel A show that, within each region, $H$-type amenities ($\overline{u}_i^H$) are higher in non-KIP than in KIP, consistent with non-KIP regions providing more amenities that are attractive to $H$-type residents. For $L$-type amenities in the center ($\overline{u}_i^L$), the value is lower in non-KIP than in KIP, consistent with KIP offering stronger informal tenure security that is valued by $L$-type residents.

Panel B additionally reports the corresponding non-KIP/KIP percentage differences in utility terms. Specifically, columns 1 and 2 report percent differences in $\Phi_i^g$ between the non-KIP and the KIP counterpart of each region, for H and L respectively, where $\Phi_i^g \equiv (u_i^g)^{\rho^g}(\overline{Y}_i^g)(r_i^g)^{(\beta_g-1)}$. Aggregating this term across regions yields our city-wide welfare metric (equation 4). The 8% figure reported in column 1 is calculated as the percentage difference in $\Phi_i^H$ between non-KIP and KIP for the center. Similarly, the -18% figure in column 2 is calculated as percentage difference between $\Phi_i^L$ for non-KIP and KIP values in the center. Overall, the pattern in amenities in Panel A translates into a monotonic pattern in the non-KIP/KIP wedges in utility terms in Panel B, columns 1 and 2.

Next, column 3 in Panel A reports $\tau$, the "tax" incurred to convert informal to formal housing, expressed as a tax rate between 0 and 1. Intuitively, the foregone profits from staying informal are greater in the center not because the tax rate is greater per se, but because the wedges in land values and heights are greater. Accordingly, Panel B reports the non-KIP/KIP percentage difference in the relative profitablity from formalization. Specifically, we calculate the profit ratio $\pi_i^{H/L} = \frac{(1-\tau_i)\pi_i^H}{(1-\tau_i)\pi_i^H + \pi_i^L}$, which governs the allocation of land between formal and informal (see equation 7). This ratio is 20% higher in non-KIP than in KIP in the center, while it is only 3% higher for the middle and 1% for the periphery.

### B.2.6 Model: robustness

Below, we report welfare gains under different assumptions for open versus closed city and strength of amenity spillovers. These results are discussed in Section 7.6.

**Table B.2:** Welfare effects of lifting KIP everywhere: robustness

| | H | L | All |
|---|---|---|---|
| Open city, spillovers, $\mu^L = 0.3\mu^H$ | 5.2% | -2.1% | 3.3% |
| Open city, no spillovers | 1.3% | -3.6% | 0.1% |
| Open city, $\mu^L = 0.5\mu^H$ | 4.5% | -1.1% | 3.0% |
| Open city, $\mu^L = 0.7\mu^H$ | 3.9% | -0.4% | 2.7% |
| Open city, $\mu^L = \mu^H$ | 3.2% | 0.1% | 2.4% |
| Closed city, spillovers | 2.5% | -3.2% | 0.9% |
| Closed city, no spillovers | 1.3% | 3.9% | -0.1% |