Sea Level Rise and Urban Adaptation in Jakarta

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January 11, 2023

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Sea level rise poses an existential threat to Jakarta, which faces frequent and worsening flooding. The government has responded with a proposed sea wall. In this setting, I study how government intervention complicates long-run adaptation to climate change. I show that government intervention creates coastal moral hazard, and I quantify this force with a dynamic spatial model in which developers and residents act with flood risk in mind. I find that moral hazard generates severe lock-in and limits migration inland, even over the long run.

Email: ajhsiao@princeton.edu. Wenqing Yu, Luong Nguyen, and Ghifari Firman provided exceptional research assistance. I am grateful to Nina Harari and Maisy Wong for their kind help in procuring data, and I acknowledge generous support from the Becker Friedman Institute International Economics and Economic Geography Initiative.

1 Introduction

Sea level rise is a major threat to economic development. Globally, 680 million people currently live in low-elevation coastal zones, with more than one billion expected by 2050 as sea levels continue to rise (IPCC 2019). The situation is especially severe in Southeast Asia, where land subsidence contributes to inundation rates that exceed those elsewhere by up to an order of magnitude.[1] Particularly vulnerable are the 31 million residents of the Jakarta metropolitan area, which is on pace to overtake Tokyo as the world's most populous megacity by 2030 (Euromonitor 2018).

Jakarta faces severe and frequent flooding, with damages exceeding $300 million annually (Budiyono et al. 2015), and sea level rise brings substantial additional risk in the years to come. In response, the Indonesian government has proposed up to $40 billion in flood infrastructure investments, including in a protective sea wall. I study how this government intervention complicates long-run adaptation by inducing moral hazard among developers. The government tends to protect development ex post despite not wanting to ex ante, and developers over-invest at the coast in anticipation of this protection. The government thus faces a commitment problem, and indeed the seminal work of Kydland and Prescott (1977) mentions flood protection as a supporting example.[2] I formalize the commitment problem in the context of sea level rise, and I show how it compounds over time to limit adaptation.

I begin by documenting how developers responded to historical government intervention. The West Flood Canal is a key part of Jakarta's existing flood infrastructure, as it diverts a major river around city center. In doing so, the canal protects areas to its north but not to its south. I measure northern and southern land development before and after the completion of the canal in 1918 by digitizing Dutch colonial maps

[1] In Southeast Asia, population-weighted rates of relative sea level rise are 3.2 times as large as those in South Asia, 11.2 times those in Russia, and 3.9 times those elsewhere (Nicholls et al. 2021). Relative sea level rise combines absolute sea level rise and land subsidence.

[2] Kydland and Prescott (1977), page 477. "For example, suppose the socially desirable outcome is not to have houses built in a particular flood plain but, given that they are there, to take certain costly flood-control measures. If the government's policy were not to build the dams and levees needed for flood protection and agents knew this was the case, even if houses were built there, rational agents would not live in the flood plains. But the rational agent knows that, if he and others build houses there, the government will take the necessary flood-control measures. Consequently, in the absence of a law prohibiting the construction of houses in the flood plain, houses are built there, and the army corps of engineers subsequently builds the dams and levees."

from 1887 to 1945. I then apply a spatial regression discontinuity design at the canal boundary in the spirit of Almond et al. (2009), who study the Huai River in China.[3] I show that the north and south are similar before the canal, but that the north experiences less flooding and more land development after the completion of the canal. That is, developers responded to government intervention by increasing investment.

I study how this response creates a commitment problem for future government intervention. I do so quantitatively with a dynamic spatial model of urban development and a focus on Jakarta's planned sea wall. In the model, developers and residents make investment and location decisions with flood risk in mind. Residential demand is spatial, as individuals make location decisions based on rents, flood risk, amenities, and migration costs. Moving inland abandons high-amenity areas and incurs migration costs. Developer supply is dynamic, as forward-looking developers make sunk investment decisions in immobile buildings. They do so trading off a stream of future rents against the upfront costs of construction. Moving inland abandons high-rent areas and incurs construction costs. Total supply arises as a dynamic competitive equilibrium among atomistic developers, as in Hopenhayn (1992), and rents clear markets for development, equalizing residential demand and developer supply in each period. The government intervenes with a sea wall, as informed by a hydrological model of how sea wall construction affects flooding across locations.

Estimation leverages granular data on developers, residents, and flooding. I estimate residential demand by matching changes in the spatial distribution of population between 2015 and 2020. Estimation mirrors Berry et al. (1995), integrating over origins and addressing the endogeneity of rents with instruments. I estimate developer supply by matching the spatial distribution of new construction between 2015 and 2020. Estimation relies on reading continuation values from data on market prices, in the style of Kalouptsidi (2014), and again addresses the endogeneity of rents with instruments. For intuition, consider the binary choice to develop or not. Property values capture the stream of rents from developing, while land values capture the option value from not (but perhaps developing in the future). Each is inclusive of market expectations, including over government intervention. Where market frictions prevent long-term revenues from capitalizing fully into prices, differencing eliminates

[3] Almond et al. (2009), along with subsequent work by Chen et al. (2013) and Ebenstein et al. (2017), compare air quality in Chinese cities to the north and south of the Huai River. Northern cities receive free coal for winter heating, while southern cities do not.

the resulting bias to the extent that it is systematic. Finally, I follow the frontier of the hydrological literature in training a machine-learning model of flooding with monthly, tract-level data on flooding from 2013 to 2020. A histogram gradient boosting decision tree fits the data well and provides sensible predictions for how sea wall construction decreases flooding over space.

In simulations, I quantify the effects of commitment on long-run coastal development and social welfare. I consider both forward-looking and politically myopic governments, and I study how relocating demand interacts with commitment. I find that non-commitment increases long-run coastal development, reducing social welfare by 78% relative to the first best achieved under full commitment. Limited commitment raises welfare, particularly when forward-looking governments internalize costs to future administrations. Relocating demand away from the coast reduces both moral hazard and welfare losses under non-commitment, and it is consistent with the moving of the political capital from Jakarta. Such a move also requires commitment, but may be more politically feasible than commitment not to intervene. Full policy counterfactuals are in progress.

My main contribution is to quantify how endogenous government intervention limits adaptation to sea level rise. Adaptation blunts the consequences of sea level rise (Balboni 2021, Desmet et al. 2021, Castro-Vincenzi 2022, Jia et al. 2022) and of climate change more broadly (Barreca et al. 2016, Costinot et al. 2016, Cruz and Rossi-Hansberg 2021, Nath 2022). Desmet et al. (2021) in particular show that moving inland can greatly reduce damages from coastal flooding. Government intervention complicates this narrative by displacing private investment in self-protection (Peltzman 1975, Kousky et al. 2006, Boustan et al. 2012, Annan and Schlenker 2015, Kousky et al. 2018, Baylis and Boomhower 2022, Fried 2022), creating moral hazard that mirrors distortions in insurance markets (Coate 1995, Mulder 2022, Ostriker and Russo 2022, Wagner 2022). Endogenizing government intervention amplifies this effect as continued coastal investment induces further government intervention. The result is severe coastal lock-in, in contrast to the smooth inland transition of Desmet et al. (2021) and consistent with the observed persistence of coastal concentration (Vigdor 2008, Kocornik-Mina et al. 2020).

Methodologically, I estimate a model of industry dynamics in the tradition of Hopenhayn (1992) and Ericson and Pakes (1995), drawing on dynamic discrete choice methods from Hotz and Miller (1993) and Arcidiacono and Miller (2011). I build on Kalouptsidi (2014), who shows how to avoid computing continuation values, at least in estimation, by reading them from data. I show how this insight greatly simplifies estimation of dynamic developer models with data generally available in urban settings, where dynamics are particularly important given the durability of development (Glaeser and Gyourko 2005). This approach accommodates developer expectations with significantly more flexibility than full-solution approaches that must specify long-run expectations, and even two-step approaches that require only rational expectations, as in the Euler conditional choice probability approach of Scott (2013). In incorporating geography, I also complement a growing literature that brings dynamics to spatial models (Desmet et al. 2018, Caliendo et al. 2019, Kleinman et al. 2022).

Finally, I provide quantitative estimates and recommendations for Jakarta, drawing on work in environmental studies that assesses current and future flood risk (Budiyono et al. 2015, Takagi et al. 2016, Wijayanti et al. 2017, Andreas et al. 2018). Land subsidence in Jakarta effectively accelerates sea level rise, bringing questions of adaptation to the fore. Jakarta thus foreshadows the future that most coastal cities will face by century's end, including as sea walls enter policy discussions worldwide.[4] Jakarta's challenges are the world's challenges.

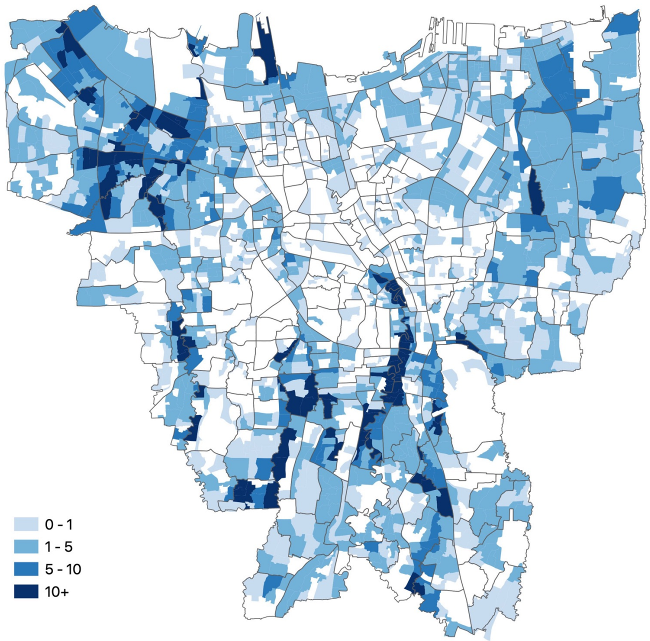
2 Background

Flooding has long plagued Jakarta. Historical records capture flooding as early as 1621, shortly after the Dutch East India Company established its capital of Batavia at the north of the present-day city (Abeyasekere 1987). Figure 1 shows that widespread flooding persists today, with major incidents in 1996, 2002, 2007, 2013, and 2020. Geography makes flooding inescapable, as Jakarta occupies a delta where thirteen rivers meet the ocean. This nexus of waters both nurtures and menaces the city.

Fluvial (river) flooding in times of extreme rainfall has been the key challenge to date. Historical flood policy thus focused on infrastructure aimed at managing river

[4] China plans 15,000 km of coastline sea wall, and Japan has built 400 km along the Tohoku coastline. The Northern European Enclosure Dam project proposes dams from France to England and Scotland to Norway. Miami has proposed 10 km of coastline sea wall, and New York has proposed the BIG U project covering Lower Manhattan.

Figure 1: Flood frequency (2013-2020)



Source: Regional Disaster Management Agency (*BPBD* via *data.jakarta.go.id*). I plot the average number of months per year with registered flood incidents by tract and boundaries by neighborhood.

water, including a westward canal (*Westerse Vaart*) in 1725, the West Flood Canal (*Banjir Kanal Barat*) in 1918, and the East Flood Canal (*Banjir Kanal Timur*) in 2002 (Caljouw et al. 2005, Ward et al. 2011, Octavianti and Charles 2019). Each operates within a broader system of dams, reservoirs, drainage systems, pumping stations, and flood gates. Figure 2 maps this infrastructure.

Coastal flooding adds significant additional risk in the coming decades. North Jakarta faces near total submersion by 2050, as sea level rise combines with rapid land subsidence. Projected subsidence in some coastal neighborhoods exceeds five meters by 2050, compared to projected sea level rise of 25 centimeters (Andreas et al. 2018, Kulp and Strauss 2019). The government has responded with two key initiatives to protect this city that drives the nation's economy.

First, a sea wall has been in discussion since 2011, with costs as high as $40 billion (Garschagen et al. 2018, Colven 2020). Proposals have varied in scope and ambition, but each has prioritized onshore walls for short-term protection. The Jakarta Coastal Defense Strategy (JCDS) in 2011 became the National Capital Integrated Coastal

Figure 2: Flood infrastructure

Source: Regional Disaster Management Agency (*BPBD* via *data.jakarta.go.id*).

Development Masterplan (NCICD) in 2014 – the so-called "Great Garuda Project" – and was further revised in 2016. Progress then slowed with a 2016 moratorium and the 2017 election of Anies Baswedan, whose gubernatorial campaign called for halting construction. Work resumed in 2019 with the Integrated Flood Safety Plan (IFSP).

Second, the government plans to establish a new political capital called Nusantara, at once hedging against flood risk and relieving congestion in Jakarta. The move to what is currently East Kalimantan province comes at a proposed cost of $32 billion, with inauguration slated for Indonesia's national day on August 17, 2024. The government envisions a planned, modern city nestled in the forests of Borneo, named in tribute to the ancestral word for the archipelago. Official goals include employment of nearly five million and net-zero emissions by 2045 (IKN 2022).

3 Theory

I show how coastal development forces government intervention both today and tomorrow, leading to over-development and over-defense.

3.1 Development and defense

I model flood-prone coastal development and the government investment aimed at defending it. In each period t, developers undertake development d_t at cost $c(d_t)$, and the government undertakes defense g_t at cost $f(g_t)$. Costs are increasing and convex. Residential value $r(D_t, g_t)$ is increasing and concave in each argument, with complementarity $\kappa = \frac{\partial^2 r}{\partial d \partial g} > 0$ and total $D_t = D_{t-1} + d_t$.[5] I model defense with physical infrastructure in mind, but it encompasses any costly government intervention that raises residential value, including flood insurance programs.[6] Dynamics arise from durable development that demands both current and future defense.[7]

In the first best, the social planner chooses development and defense over time to maximize social welfare. The government also aims to maximize welfare, but frictions arise as it only directly chooses defense. Development is instead chosen by developers with private profits in mind. Welfare is

$$W_t = \sum_{t'=0}^{T-t} \beta^{t'} w_{t+t'}, \quad w_t = r(D_t, g_t) - c(d_t) - f(g_t)$$

for net present value W_t and current w_t. Similarly, define

$$X_t = \sum_{t'=0}^{T-t} \beta^{t'} x_{t+t'} \quad \text{for} \quad x_t \in \{r(D_t, g_t), c(d_t), f(g_t)\}.$$

Developers do not internalize the costs of defense, implying profits

$$\pi_t = \frac{\partial}{\partial d_t}(R_t - c_t)$$

for the marginal developer given $c_t = c(d_t)$. Revenues are $\frac{\partial}{\partial d_t} R_t$ and costs $\frac{\partial}{\partial d_t} c_t$. The

5 For costs, $\frac{dc}{dd}, \frac{d^2c}{dd^2}, \frac{df}{dg}, \frac{d^2f}{dg^2} > 0$. For $r(D, g)$, $\frac{\partial r}{\partial d}, \frac{\partial r}{\partial g} > 0$ and $\frac{\partial^2 r}{\partial d^2}, \frac{\partial^2 r}{\partial g^2} < 0$ given $\frac{\partial}{\partial d} = \frac{\partial}{\partial D}$. Fixing g_t, $r(D_t; g_t)$ captures downward-sloping residential demand. It measures the area under the demand curve for development $[0, D_t]$. The demand curve itself is $r'(D_t; g_t)$. Higher g_t shifts demand upward, subject to diminishing marginal returns to g_t.

6 Coastal flooding presents recurring aggregate risk, limiting the role of risk aversion or sharing. As such, flood insurance programs raise residential value only insofar as they under-price and thus subsidize risk. Like infrastructure, such subsidies are coastal transfers.

7 For simplicity, I consider nondurable defense with repeated intervention. Such a model is isomorphic to one with durable defense but repeated intervention due to rising sea levels.

social planner maximizes W_t, as does a forward-looking government. A politically myopic government maximizes $R_t - c_t - f_t$, weighing future benefits but ignoring future costs. Such a government may value political credit for future resident welfare, or it may experience lobbying by forward-looking developers. Developers consider profits, with $\pi_t = 0$ under perfect competition.

3.2 Commitment

Over-development arises when the government lacks commitment power. The government tends to defend development ex post despite not wanting to ex ante, and developers take advantage to force defense at suboptimally high levels. Setting $D_0 = 0$ for simplicity, consider the one-period case with social welfare

$$W = r(d, g) - c(d) - f(g).$$

In the first best, the social planner chooses development and defense to maximize social welfare. The resulting first order conditions are

$$\begin{aligned} &[d^*] \quad r'(d) = c'(d), \\ &[g^*] \quad r'(g) = f'(g) \end{aligned}$$

for $r'(x) = \frac{\partial}{\partial x} r(d, g)$. Both lines equalize marginal benefits and costs.[8]

Without commitment, the government revises its choice of defense after development is sunk, and developers act anticipating this response. In equilibrium,

$$[d^n] \quad r'(d) + r'(g)\, g'(d) = c'(d), \tag{1a}$$

$$[g^n] \quad r'(g) = f'(g). \tag{1b}$$

Equation 1a equalizes marginal revenues and costs, as developers are perfectly competitive, while equation 1b remains as above.[9] First, defense responds to sunk devel-

[8] The same analysis also captures a world in which defense is durable and requires only one-time investment, with welfare components r, c, and f capturing net present values.

[9] Atomistic marginal developer d does not itself affect residential values or defense. But its revenues $r'(d) + r'(g)\, g'(d)$ are set by mass $[0, d)$ of inframarginal developers, as in the typical zero-profit condition in which entrants affect prices collectively but not individually.

opment. Differentiating equation 1b with respect to development,

$$\kappa + r''(g)\, g'(d) = f''(g)\, g'(d).$$

It follows that $g'(d) > 0$ given $\kappa > 0$, $r''(g) < 0$, and $f''(g) > 0$. Second, this response creates moral hazard, as over-development anticipates over-defense. In equation 1a, $r'(g)\, g'(d) > 0$ implies $d^n > d^*$ given $r''(d) < 0$ and $c''(d) > 0$. Moral hazard raises developer returns and thus development.

Commitment avoids over-development. Committing to first-best defense g^* yields $g'(d) = 0$, eliminating moral hazard. The challenge is that the government finds it optimal to protect over-development ex post, particularly if lobbying or upcoming elections increase its returns to doing so. An alternative is to target first-best development d^* by committing to tax $f(g)$ on development. The tax forces developers to internalize the costs of defense, implying profit condition

$$r'(d) + r'(g)\, g'(d) - f'(g)\, g'(d) = c'(d),$$

which coincides with the social planner's first order condition given equation 1b. Restricting permits or zoning achieves similar outcomes by regulating quantities instead of prices. The challenge is that developers will lobby against enforcement of taxes and restrictions, particularly if lobbying is facilitated by corruption.

3.3 Commitment over time

With two periods, the social planner chooses development and defense across periods to maximize welfare $W_1 = w_1 + \beta w_2$. The first order conditions are

$$\begin{aligned}
&[d_1^*] \quad r_1'(d_1) + \beta r_2'(d_1) = c'(d_1),\\
&[g_1^*] \quad r_1'(g_1) = f'(g_1),\\
&[d_2^*] \quad r_2'(d_2) = c'(d_2),\\
&[g_2^*] \quad r_2'(g_2) = f'(g_2)
\end{aligned}$$

for $r_t'(x) = \frac{\partial}{\partial x} r(D_t, g_t)$. The government achieves this first best under full commitment, which allows it to set (d_1, g_1, d_2, g_2) and thus to act as social planner.

Without commitment in period two, the government chooses g_2 to maximize welfare W_2, and developers choose d_2 considering profits π_2. The resulting equilibrium conditions mirror equations 1.

$$[d_2^n] \quad r_2'(d_2) + r_2'(g_2)g_2'(d_2) = c'(d_2), \tag{2a}$$

$$[g_2^n] \quad r_2'(g_2) = f'(g_2) \tag{2b}$$

Period one depends on government commitment and horizon. For development, limited commitment allows the government to choose d_1 in period one. A forward-looking government (^{f}) maximizes W_1, while a politically myopic government (^{m}) maximizes $R_1 - c_1 - f_1$. No commitment implies that developers set d_1 with π_1 in mind. Each case anticipates no commitment in period two.

$$[d_1^f] \quad r_1'(d_1) + \beta r_2'(d_1) = c'(d_1) + \beta r_2'(g_2)g_2'(d_1), \tag{3a}$$

$$[d_1^m] \quad r_1'(d_1) + \beta r_2'(d_1) + \beta r_2'(d_2)d_2'(d_1) + \beta r_2'(g_2)g_2'(d_1) = c'(d_1), \tag{3b}$$

$$\begin{aligned}[d_1^n] \quad & r_1'(d_1) + \beta r_2'(d_1) + \beta r_2'(d_2)d_2'(d_1) + \beta r_2'(g_2)g_2'(d_1) \\ & + r_1'(g_1)g_1'(d_1) = c'(d_1)\end{aligned} \tag{3c}$$

For defense, the government chooses g_1, and the same first order condition holds for both forward-looking and politically myopic governments.[10]

$$[g_1] \quad r_1'(g_1) = f'(g_1) \tag{3d}$$

Moral hazard arises both within and across periods. Within periods, developers exploit the government. Both $r_2'(g_2)g_2'(d_2) > 0$ in period two (equation 2a) and $r_1'(g_1)g_1'(d_1) > 0$ in period one (equation 3c) prompt over-development that forces over-defense. Across periods, current developers exploit the future government. In period one, $r_2'(d_2)d_2'(d_1), r_2'(g_2)g_2'(d_1) > 0$ (equation 3c) prompts current over-development that forces future over-defense. Similarly, a politically myopic current government exploits the future government, as the same terms (equation 3b) lead to current over-investment given uninternalized future costs.

[10] Although $d_2'(d_1), g_2'(d_1) > 0$, the chain rule and $d_1'(g_1) = 0$ imply $d_2'(g_1) = g_2'(g_1) = 0$. With commitment, $d_1'(g_1) = 0$ given joint optimization over (d_1, g_1). Without commitment, $d_1'(g_1) = 0$ because developers set d_1 before the government chooses g_1.

Furthermore, development has persistent effects. On one hand, this persistence creates lock-in at the coast. Over-development in period one prompts over-defense in period two, as the government seeks to protect sunk $d_1 > d_1^*$.[11] The result is over-development in period two, even when the period-two government has commitment power. On the other hand, this persistence allows the current government to help future governments. In period one, $r_2'(g_2)g_2'(d_1) > 0$ (equation 3a) induces under-defense that reduces moral hazard and the resulting over-defense in period two. The current government moves before future developers and thus shapes their actions.

As before, commitment avoids over-development. Commitment to first-best defense (g_1^*, g_2^*) eliminates moral hazard, as does commitment to taxes or restrictions targeting first-best development (d_1^*, d_2^*). Commitment demands that the government resist its static incentives – as well as lobbying – not only in period one, but also in period two. More generally, the challenge is that commitment avoids over-development only if it holds over the long run. Even if the current government has commitment power, over-development proceeds if a future government does not.

Alternative policies constrain long-run development more indirectly. Lower coastal demand reduces the returns to defense, decreasing the responsiveness of defense to development and thus lessening moral hazard. The government can lower coastal demand by relocating residents with direct mandates, migration subsidies, or improving non-coastal amenities. Such policies may be more politically feasible over the long run than direct attempts to regulate development, and they can have persistent effects even if implemented temporarily. Capital destruction can also constrain long-run development. A smaller stock of development reduces the need for defense, which lowers new development. But it also increases the extent to which new development drives defense, thereby raising moral hazard. Appendix A considers extensions.

4 Empirics

I outline a framework for the empirics, describe the data, and show how developers responded to historical government intervention.

[11] Downward-sloping demand generates an opposing force, as $d_2'(d_1) < 0$ is possible if the negative effect of $r_2'(d_2; d_1)$ dominates the positive effect of $r_2'(d_2; g_2(d_1; D_0))$. For large stock D_0, however, lock-in via defense $g_2(d_1; D_0)$ will dominate.

4.1 Framework

The theory above frames the empirical analysis. Consider components $r(d, g)$, $c(d)$, and $f(g)$ of social welfare given development and defense (d, g) in the one-period case. I obtain residential value $r(d, s(g))$ as a function of development and flood safety by estimating a model of residential demand, where development demanded is decreasing in price and increasing in flood safety s. I obtain costs $c(d)$ of development by estimating a model of developer supply, where development supplied is increasing in price and decreasing in costs of construction. I obtain flood safety $s(g)$ with a machine-learning-based hydrological model of flood risk, which I train on observed flooding data. I obtain costs $f(g)$ of defense from engineering estimates.

4.2 Data

I compile high-resolution spatial data on building construction, populations, real estate values, and flooding across Jakarta at the tract level. Jakarta consists of five districts (*kota*), 44 sub-districts (*kecamatan*), 267 neighborhoods (*kelurahan*), and 2,722 tracts (*rukun warga*).[12] Each tract contains around 4,000 people. Figure 3 illustrates the data, and appendix B provides additional detail.

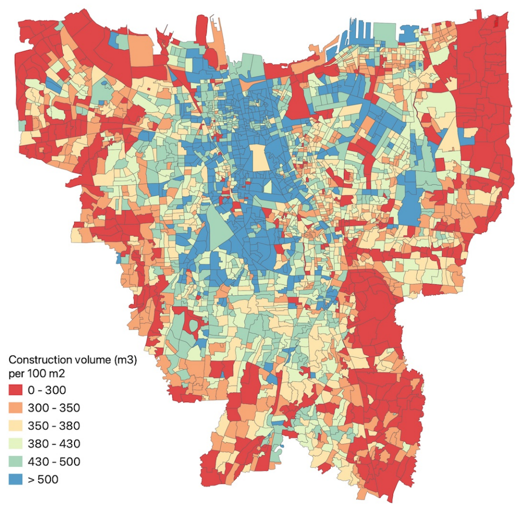
The Global Human Settlement Layer measures building construction and populations across Jakarta (GHSL 2022). It does so at the 100m grid cell level every five years from 1975 to 2020. The construction data record built-up surface areas and volumes, separating residential from non-residential construction. I verify the 2015 measures by comparing them to 2015 data from Visicom, a provider of satellite-derived 3D maps that capture building heights at the 1m pixel level. When aggregated by tract, the correlation between the datasets exceeds 0.90. The population data are downscaled from regional administrative data based on the distribution and density of residential buildings, as measured in the construction data. This approach assumes that residents occupy development, consistent with my empirical model in which rents clear markets for development in equilibrium.

Real estate values include property and land values, where property values include constructed buildings. I construct property values for 2015 by combining data

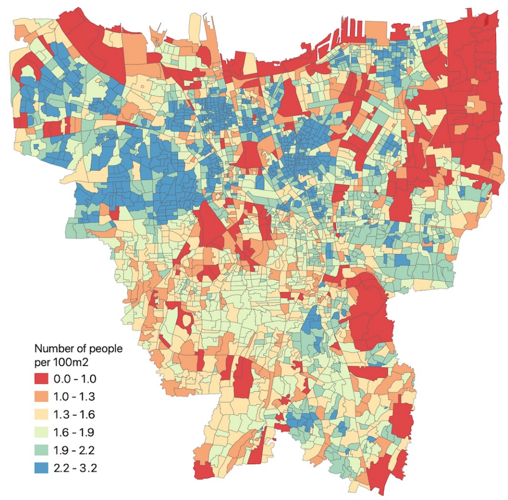
[12] I focus on Jakarta proper, although the empirical analysis accounts for movement across the broader metropolitan area. I exclude the islands of *Kepulauan Seribu* district.

Figure 3: Data (2015)

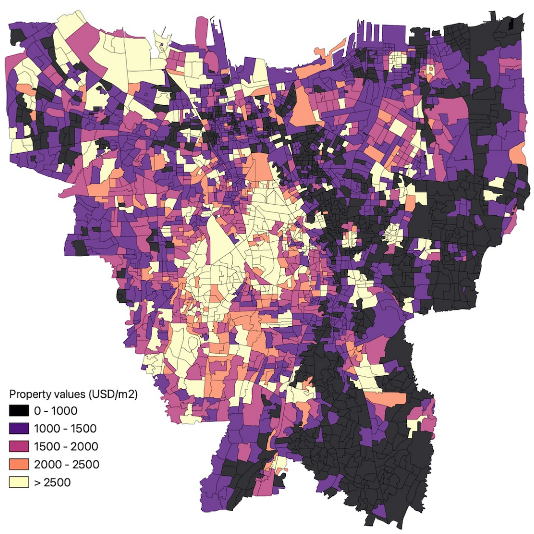
(a) Building construction



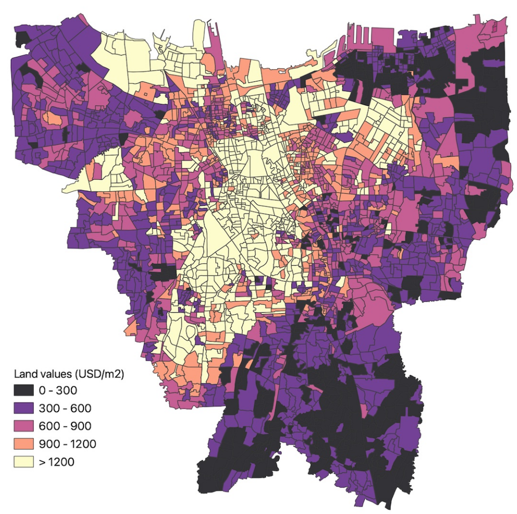
(b) Population



(c) Property value



(d) Land value



Building construction and populations come from the Global Human Settlement Layer. I construct property values with transactions and listings data from 99.co and brickz.id. Land values come from the Smart City initiative of the Jakarta city government.

on property transactions and listings from two major real estate websites, 99.co and brickz.id, covering both residential and non-residential properties. From 99.co, I scrape and geocode 56,222 listings with prices and floor spaces for October 2022. I compute property values as prices per square meter of floor space, then I aggregate to the tract level. From brickz.id, I obtain 6,929 property transactions for 2015. I use these data to backcast the 2022 property values and to adjust for differences between listed and transacted prices. I thus obtain transacted property prices for 2015.

Land values for 2015 come from the Jakarta Smart City initiative, through which the city government and the National Land Agency (*Badan Pertanahan Nasional*) sought to update property tax appraisals and improve collections. They did so by computing land values at a granular level, drawing on administrative data from transactions, market data from brokers and online platforms, and property characteristics from field visits. The data include 20,892 observations at the sub-block level, with land values measured as prices per square meter. I aggregate to the tract level. Harari and Wong (2019) describe these data in further detail and take additional steps to verify the quality of the data, including in informal areas.

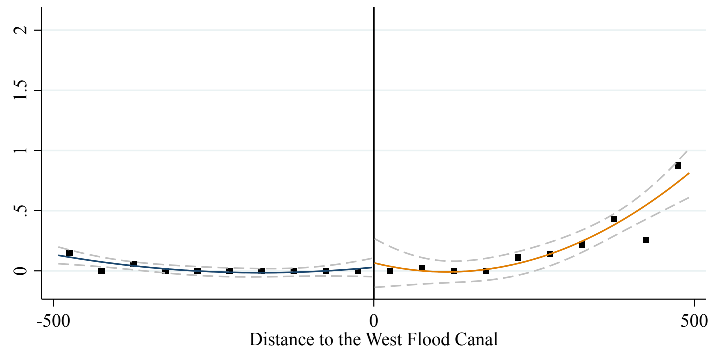
Flooding data come from the Regional Disaster Management Agency and measure realized flooding from 2013 to 2020. For each month during this period, I observe the tracts that experienced flooding, the depth and duration of flooding, and the number of people affected. I use these data to compute measures of flood frequency and depth. I do so for each tract as follows. For flood frequency, I count the number of months in each year with flooding, then I average across years. Figure 1 maps these frequencies. For flood depth, I sum over the monthly flood depths in each year, then I again average across years.

4.3 Historical government intervention

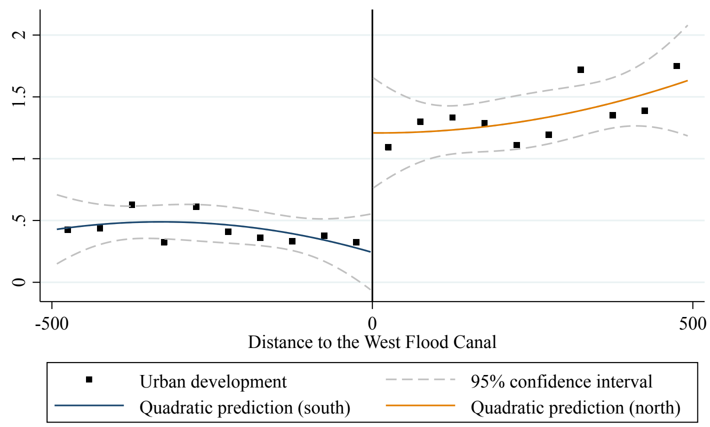
I consider whether historical investments in flood protection led to higher levels of land development. The opening of the West Flood Canal in 1918 allows me to study this dynamic over the last century, with historical maps from the Dutch colonial era providing measures of land development both before and after the construction of the canal. I georeference eight maps that cover the period from 1887 to 1845 in six- to eight-year intervals. I digitize them to construct a panel that records, over time, whether each 50m cell contains developed or undeveloped land. I then aggregate to the 100m cell by counting the developed 50m cells within each 100m cell. This aggregation allows me to accommodate misalignment over time, which otherwise introduces conflicting measures of development from year to year.

Figure 4: Land development and the West Flood Canal

(a) Before (1910)



(b) After (1945)



Data on historical land development come from Dutch colonial maps. The West Flood Canal was completed in 1918 and protected neighborhoods to its north (positive distances), but not to its south (negative distances). Each observation is a 100m grid cell. The x-axis measures distance to the West Flood Canal in meters, and 500m is the optimal bandwidth.

I restrict attention to cells in the vicinity of the West Flood Canal, dropping those located directly on the canal boundary, and I plot land development relative to distance to the canal. In doing so, I leverage the spatial discontinuity in flood risk arising from the construction of the canal, which protected neighborhoods to its north but not to its south. Figure 4 shows the results: land development jumps at the boundary after the opening of the canal, but not before, as building development responds positively to increased flood protection. Appendix B shows the associated regression table, documents increased flooding to the north of the boundary, and shows smoothness in elevation across the boundary, as well as smoothness in land development in all observed pre-canal years.

This spatial discontinuity approach is subject to several potential concerns. First, the government may have anticipated future land development when placing the canal. But it seems difficult to target development 30 years in the future, and also to target finely enough to distinguish among 100m cells. Second, flood risk may not be the only driver of post-canal differences in northern and southern land development. The north is closer to city center, which grows more quickly than the periphery, but differences in proximity are minimal when restricting attention around the boundary. I also show the absence of pre-canal differences in growth. The canal may itself impose a physical barrier between north and south, but 15 crossings minimize the separation between north and south over the 10 km stretch of canal that I study.[13]

5 Demand

Residents determine the demand for development. They choose locations with flood risk in mind, and estimation matches changes in population shares.

5.1 Model

Residents make static location choices over space. For an individual i in origin j considering destination k, utility is

$$U_{ijk} = \underbrace{-\alpha r_k + \rho s_k + \xi_k}_{\delta_k} - \tau m_{jk} + \epsilon_{ijk} \tag{4}$$

for rent r_k, flood safety s_k, amenity ξ_k, migration distance m_{jk}, logit shock ϵ_{ijk}, and destination-specific utility δ_k. Residents seek low rents, high flood safety, high amenities, and short distances. Distance introduces spatial dependence.[14] Residential

[13] A more subtle concern is that the canal affected government investment by providing a clear separation of favored and unfavored neighborhoods. The prime example of such favoritism is the once-European neighborhood of Menteng, which canal construction explicitly sought to protect. First, I see increased land development not only in favored Menteng, but also in other northern neighborhoods along the canal. Second, offsetting forces may reduce bias. On one hand, additional non-flood intervention in Menteng would lead to overstated benefits of reduced flood risk. On the other hand, additional flood assistance would lead to understated benefits.

[14] Although all origins respond proportionally to changes in destination characteristics given IIA substitution, migration from faraway origins is low at baseline because the disutility of distance dominates. Random coefficients would strengthen spatial dependence, as (α_j, ρ_j) coefficients that depend on distance would relax IIA and allow nearby origins to respond disproportionately to

demand sums over origins given populations n_j and choice probabilities p_{jk}^{res}. The development demanded by residents in each tract is thus

$$D_k^{\text{res}} = \sum_j n_j p_{jk}^{\text{res}} \phi, \quad p_{jk}^{\text{res}} = \frac{\exp(\delta_k - \tau m_{jk})}{\sum_{\hat{k}} \exp(\delta_{\hat{k}} - \tau m_{j\hat{k}})} \tag{5}$$

given floor space ϕ per resident. Moving inland is costly because it abandons high-amenity tracts and incurs migration costs. Price endogeneity arises because rents are correlated with unobserved amenities.

5.2 Estimation

I estimate demand by matching changes in the spatial distribution of population between 2015 and 2020. I address the endogeneity of rents by instrumenting with ruggedness, which shifts supply by affecting the ease of construction. I take rents to be mortgage payments on observed property values. Populations in 2015, augmented by a uniform growth rate between 2015 and 2020, define origin populations. I focus on residential choice within the core of Jakarta, but I include the option of a location that aggregates over the periphery.[15] Total metropolitan population evolves exogenously.

Estimation follows Berry (1994) and Berry et al. (1995), except that I integrate over origins instead of over a broader set of demographics. I estimate $\theta = (\theta_1, \theta_2)$ for $\theta_1 = (\alpha, \rho)$ and $\theta_2 = \tau$. First, fixing θ_2, I match observed and model-implied populations by computing $\delta = \{\delta_k\}$ by contraction mapping.[16] Suppressing dependence on data (n, m), equation 5 implies

$$\text{population}_k = \frac{1}{\phi} D_k^{\text{res}}(\delta, \theta_2).$$

Second, I regress $\hat{\delta}$ on data (r, s) to obtain estimates $\hat{\theta}_1$ and residuals $\hat{\xi}$.

$$\xi_k = \delta_k + \alpha r_k - \rho s_k$$

changes in destination characteristics.

[15] I take this periphery to be free of flood risk and to have rents set at the minimum observed within the core. Individuals originating at the periphery face distance m_{0k} to destination k defined as the minimum distance from k to the core-periphery border.

[16] Intuitively, $\text{population}_k > D_k^h(\delta_k^h)$ at iteration h is remedied by $\delta_k^{h+1} > \delta_k^h$ at $h + 1$.

Table 1: Residential demand estimates

IV	Population	First stage	Rents
Rents	-0.113***	Ruggedness	0.010***
	(0.019)		(0.001)
Flood safety	1.031**	Flood safety	7.888**
	(0.507)		(4.018)
Coastal distance	-0.072***	Coastal distance	-0.630***
	(0.016)		(0.082)
District FE	x	District FE	x
Observations	2,181	Observations	2,181
		F-stat	76.38

Each column is one regression. The left panel shows the IV regression, and the right panel shows the first stage. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Third, I compute the GMM objective function

$$Q(\theta) = g(\xi(\theta))' W g(\xi(\theta))$$

for weighting matrix W and sample analog $g(\xi(\theta)) = \sum_k Z_k \xi_k(\theta)$ of moment condition $\mathbb{E}[Z\xi(\theta)] = 0$. Fourth, I search over θ_2 to minimize $Q(\theta)$.

$$\hat{\theta}_2 = \arg\min_{\theta_2} Q(\theta_1(\theta_2), \theta_2)$$

5.3 Estimates

Table 1 presents the demand estimates. Demand is decreasing in rents, as is consistent with downward-sloping demand, and is increasing in flood safety and coastal proximity, which residents view as amenities. The flood safety coefficient is important for quantifying the welfare effect of a sea wall that increases flood safety, and the rent coefficient helps in monetizing this welfare effect. The first stage supports the validity of the instrument. Ruggedness increases the costs of construction and thus increases rents, with a large F-statistic showing the strength of the instrument.

One concern is that flooding is correlated with water-related amenities, as coastal proximity may bring both positive amenity value and increased flooding. Not controlling for this proximity thus attenuates the estimated effect of flooding on residential demand. I separate such amenities from flooding by controlling for neighborhood fixed effects and distance to the coast. Including more controls reduces the bias from uncaptured amenities, but it also reduces the remaining variation in flooding. Another approach is to rely on discontinuities in flood risk maps (Bakkensen and Ma 2020), but I focus on observed flooding that varies smoothly over space rather than flood risk measures from government maps.

Another concern is that ruggedness may violate the exclusion restriction by affecting demand directly. I argue that ruggedness is not especially salient to residents of Jakarta, where many live above ground floor in multi-story buildings and where walking activity is particularly limited (Althoff et al. 2017, Cochrane 2017). Jakarta is also relatively flat, unlike cities like San Francisco where large hills affect daily life. At the same time, developers are still sensitive to mild ruggedness because structural integrity requires laying flat foundations. Where residents do view ruggedness as a disamenity, the exclusion restriction remains satisfied if the resulting costs are borne by developers. If ruggedness affects earthquake safety, for example, then developers will either invest in earthquake-safe construction or be penalized with lower sales prices. Indeed, perfect competition among atomistic sellers – as I assume in the supply model to follow – will be consistent with such behavior.

6 Supply

Forward-looking developers make investment decisions with current and future rents in mind. Estimation substitutes data for computing continuation values.

6.1 Model

Developers make forward-looking investment choices in dynamic competitive equilibrium. Developers are atomistic and each control one tract k. They choose whether to develop and the extent of development in each period t. Development is sunk and immobile. State $w_t = (D_t, G_t)$ tracks development $D_t = \{D_{kt}\}$ and defense $G_t = \{G_{kt}\}$ by tract. For $\mathbb{E}_{kt}[\cdot] = \mathbb{E}_k[\cdot|w_t]$,

$$V_k(w_t) = r_k(w_t)D_{kt} + \mathbb{E}_{kt}[\max\{v_k^1(w_t) + \epsilon_{kt}^1, v_k^0(w_t) + \epsilon_{kt}^0\}]. \tag{6}$$

Developers choose to develop or not subject to logit shocks ϵ_{kt}. Expectations are over these shocks. The choice-specific conditional value functions are

$$v_k^1(w_t) = v_k^1(d_{kt}^*, w_t), \tag{7a}$$

$$v_k^0(w_t) = \beta \mathbb{E}_{kt}[V_k(w_{t+1}) \,|\, 0]. \tag{7b}$$

Choosing not to develop leads to the same choice in the next period, with expectations over the next-period state and $D_{kt+1} = D_{kt}$ given $d_{kt} = 0$. Choosing to develop implies a choice over the extent d_{kt} of development.

This choice over d_{kt} trades off the increased revenue from added floor space against the higher cost of constructing it.

$$v_k^1(d_{kt}, w_t) = -c_{kt}(d_{kt}) + \beta \mathbb{E}_{kt}[V_k(w_{t+1}) \,|\, d_{kt}],$$
$$c_{kt}(d_{kt}) = \left(\frac{1}{2}\psi d_{kt} + x_{kt}\gamma\right) d_{kt} + \zeta_{kt}$$

Upfront costs c include convexities ψ, observed x_{kt}, and unobserved ζ_{kt}.[17] Revenues come from stock D_{kt+1} of rentable development, with $D_{kt+1} = D_{kt} + d_{kt}$ given new d_{kt}. Flow costs are passed onto residents and thus capitalize into rents. Time to build is one period, and expectations are over future states.

$$d_{kt}^* = \arg\max_{d_{kt}} \{v_k^1(d_{kt}, w_t)\} = \frac{1}{\psi}\left(- x_{kt}\gamma + \sum_{t'=1}^{\infty} \beta^{t'} \mathbb{E}_{kt}[r_k(w_{t+t'})]\right)$$

Developers seek high rents and low costs. Developer supply sums over old and new supply given probability p_{kt}^{dev} and extent d_{kt}^* of development. The development supplied by developers in each tract is thus

$$D_{kt+1}^{\text{dev}} = D_{kt} + d_{kt}^* p_{kt}^{\text{dev}}, \quad p_{kt}^{\text{dev}} = \frac{\exp\{v_k^1(w_t)\}}{\exp\{v_k^1(w_t)\} + \exp\{v_k^0(w_t)\}} \tag{8}$$

I impose that $p_{kt}^{\text{dev}} = 0$ if $D_{kt} + d_{kt}^*$ exceeds upper bound $\bar{D}_k$ of development. Moving inland is costly because it abandons high-rent tracts and incurs construction costs. Price endogeneity arises because rents are correlated with unobserved construction

[17] Cost factors can include flood safety s_{kt} if flood protection generates upfront costs.

costs. In equilibrium, rents equalize the development demanded by residents and supplied by developers in each tract k.

$$D_{kt}^{\text{res}} = D_{kt}^{\text{dev}}$$

6.2 Estimation

I estimate supply by matching the spatial distribution of new construction between 2015 and 2020. I address the endogeneity of rents by instrumenting with resident demographics, which shift local demand for development.[18]

Estimation involves applying the logit inversion, then reading continuation value from the data in the spirit of Kalouptsidi (2014). Inverting equation 8,

$$\ln p_{kt}^{\text{dev}} - \ln\big(1 - p_{kt}^{\text{dev}}\big) = v_k^1(w_t) - v_k^0(w_t). \tag{9}$$

Substituting equations 7,

$$v_k^1(w_t) - v_k^0(w_t) = -c_{kt}(d_{kt}^*) + \beta\mathbb{E}_{kt}[V_k(w_{t+1}) \,|\, d_{kt}^*] - \beta\mathbb{E}_{kt}[V_k(w_{t+1}) \,|\, 0],$$

where development d_{kt}^* is as observed in the construction data. If future profits capitalize into real estate prices, then price data capture the forward-looking terms and sidestep the challenge of computing continuation values. For prices P_{kt}^1 per square meter of development and P_{kt}^0 per square meter of land required for development,

$$\begin{aligned}
\beta\mathbb{E}_{kt}[V_k(w_{t+1}) \,|\, d_{kt}^*] &= P_{kt}^1(D_{kt} + d_{kt}^*) + P_{kt}^0(\bar{D}_k - D_{kt} - d_{kt}^*) + \eta_{kt}^1, \\
\beta\mathbb{E}_{kt}[V_k(w_{t+1}) \,|\, 0] &= P_{kt}^1 D_{kt} + P_{kt}^0(\bar{D}_k - D_{kt}) + \eta_{kt}^0.
\end{aligned}$$

Real estate prices reflect the stream of future rents embodied in value function V_k, up to expectational errors η_{kt} given information set $\mathcal{J}_{kt}$. Developed land generates rents, while undeveloped land has the option value of future development. For $\Delta X_{kt} = X_{kt}^1 - X_{kt}^0$, I thus obtain estimating equation

$$\ln p_{kt}^{\text{dev}} - \ln\big(1 - p_{kt}^{\text{dev}}\big) = -c_{kt}(d_{kt}^*) + \Delta P_{kt} d_{kt}^* + \Delta\eta_{kt}. \tag{10}$$

[18] Resident demographics also capture local labor, which directly affects supply. For robustness, I can construct demographics omitting low-income, construction-sector residents.

This approach relies on several key assumptions. First, developers are independent and atomistic. The challenge is that entry by large developers changes real estate prices from observed values. That is, equation 10 has P^1_{kt} and P^0_{kt} that are conditional on present and future development $\{d^*_{kt}, d^*_{kt+1}, \ldots\}$, but v^1_k and v^0_k involve entry that departs from this path. Second, I require real estate data on both property and land values. Such data are available for Jakarta and likely many other urban settings, although perhaps less so for rural settings. Third, I require that these real estate data accurately capture the continuation values of interest. Other work has documented how flood risk may not fully capitalize into housing prices, and I discuss below how my approach can at least partially accommodate such frictions.

An alternative is an Euler conditional choice probability approach, applying methods from Scott (2013) that I build on in previous work (Hsiao 2022). The intertemporal comparison between developing today and tomorrow implies an estimating equation that I derive in appendix C. Like the baseline approach, it avoids computing continuation values by appealing to finite dependence as in Arcidiacono and Miller (2011). It also requires atomistic developers: actions by a large developer prompt reactions by other developers, shifting the evolution of the economy and causing finite dependence to fail. Unlike the baseline approach, the Euler approach requires data in both periods t and $t+1$, as well as on rents.[19] The Euler approach cannot accommodate depreciating development, while the baseline approach can. The Euler approach also requires long-lived developers that control land for multiple periods and thus can choose the timing of development. By contrast, the baseline approach is isomorphic to short-lived entrants that buy land, develop, and sell before exiting the market. More broadly, the focus is on periods t versus $t+1$ in the Euler approach, instead of property versus land values in the baseline approach.

Both approaches flexibly accommodate future expectations, including over government intervention that is particularly salient in my context. The Euler approach appeals to rational expectations among developers, which allows long-run expectations to difference out. It thus accommodates expectations without the need to specify them explicitly. The baseline approach weakens rational expectations in two ways. First, it relies only on rational expectations at the level of the market, rather than for each individual developer. Optimistic developers will lower prices as rational

[19] Data on property values are sufficient if one assumes that rents mirror mortgage payments.

competitors undercut them, while pessimistic developers will raise prices as rational arbitragers compete to claim profits. An efficient market thus ensures that asset prices reflect underlying value. Second, it relies only on the difference between property and land values, such that common bias cancels.[20] Indeed, such bias can include flood risk that does not fully capitalize into real estate values. Differential bias loads onto cost parameters, which counterfactuals hold fixed.

At the same time, accommodating non-atomistic agents remains difficult. Market power complicates both Euler and baseline estimation, and it greatly increases the computational burden of solving the model for counterfactuals. However, offsetting mechanisms may limit bias. Under-development arises from typical price-setting incentives, while over-development arises as market power increases developers' influence on government intervention. Furthermore, each force is muted by the stock of existing development. I therefore abstract from market power in the baseline approach, although I can accommodate it in a reduced-form way in assessing robustness.[21]

The dynamic discrete choice literature broadly offers two other approaches. The full-solution approach, following the nested-fixed point algorithm of Rust (1987), requires computing continuation values and solving the model repeatedly. It is thus computationally intensive and requires specifying expectations explicitly. The specifying of expectations, including over the far-out future, is much stronger than assuming rational expectations by either individuals or the market. Two-step approaches, as reviewed in Ackerberg et al. (2007), simplify computation by estimating continuation values nonparametrically from the data in a first step, then estimating model parameters in a second step.[22] However, the first step requires a recurrent class of states that my non-stationary model does not achieve.

[20] That is, $\Delta\eta_{kt} = \eta^1_{kt} + \bar{\eta}_{kt} - \eta^0_{kt} - \bar{\eta}_{kt}$ remains unaffected by common bias $\bar{\eta}_{kt}$.

[21] An imperfect but simple way of capturing market power is with the ratio of new relative to existing development. This ratio can enter as a cost factor, or alternatively as an adjustment to expected real estate prices. In the second approach, I can estimate the observed relationship between this ratio and real estate prices. In both approaches, extensive new development places downward pressure on prices. Neither approach fully models the effects of market power on the broader dynamic game, but each retains computational tractability.

[22] Hotz and Miller (1993) and Hotz et al. (1994) develop such methods in the single-agent setting. Rust (1994) suggests extending these insights to multiple-agent games, and Jofre-Benet and Pesendorfer (2003), Aguirregabiria and Mira (2007), Bajari et al. (2007), Pakes et al. (2007), and Pesendorfer and Schmidt-Dengler (2008) show how to do so.

7 Government

I consider government intervention under a range of assumed levels of commitment and political turnover. Engineering estimates determine the associated costs $f(G_t)$ of this intervention. Intervention increases flood safety in affected cells, raising resident demand and thus rents in these cells. Higher rents induce increased developer supply, which in turn attenuates the rise in rents. Defense is durable and follows

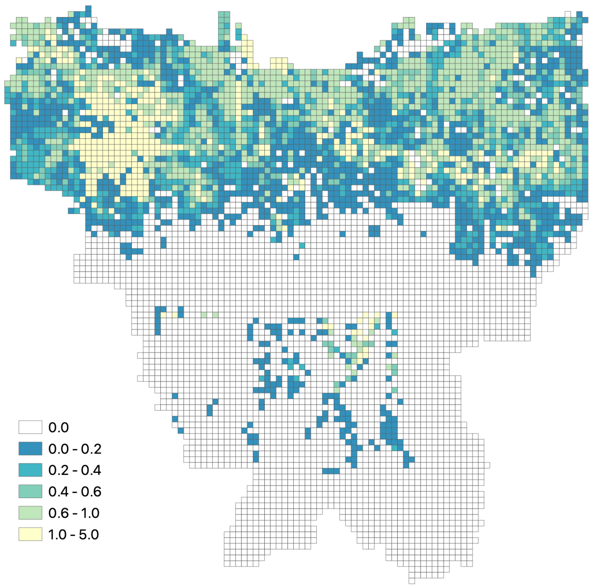
$$G_{kt+1} = G_{kt} + g_{kt}.$$

7.1 Flooding

A hydrological model of flooding captures how flood safety $s(G_{kt})$ responds to any given mode of government intervention G_t. I adopt a machine-learning approach to modeling flooding, following the frontier in hydrology as reviewed by Mosavi et al. (2018). I train and validate the model on observed flooding from 2013 to 2020, which I measure monthly and at the tract level. As input data, I use rainfall, elevation, slope, and distances to major rivers, minor rivers, and the coast. I train a range of machine learning models and find that a histogram gradient boosting decision tree performs best. I impose monotonicity constraints on distance to major rivers and elevation, which help to reduce overfitting by applying basic physical properties without the complexity of modeling the full physical system. Appendix C describes this procedure in detail.

The trained model allows me to simulate how a sea wall would affect flooding across Jakarta. Figure 5 shows the impact of a three-meter sea wall, which I simulate by raising the elevation of the city relative to sea level. The predictions align with intuition. The coastal north benefits most from the sea wall, with especially large reductions in flooding in low-elevation areas. Some parts of the high-elevation south also benefit, as greater drainage in the north alleviates flooding near river banks in the south. Indeed, the machine learning model captures this interaction without an explicit model of the complex physical processes that determine river drainage.

Figure 5: Reductions in flood frequency for a 3m sea wall



I map reductions in flood frequency, as measured in months per year, following the construction of a 3m sea wall. I simulate the sea wall by raising elevation and using the trained hydrological model to compute changes in flood frequency over space.

8 Counterfactuals

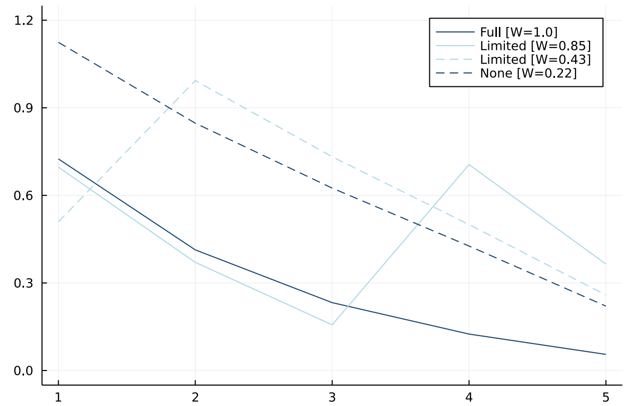
I simulate how coastal development and defense vary with government commitment, and I show how relocating demand affects the commitment problem. Full policy counterfactuals are in progress.

8.1 Simulations

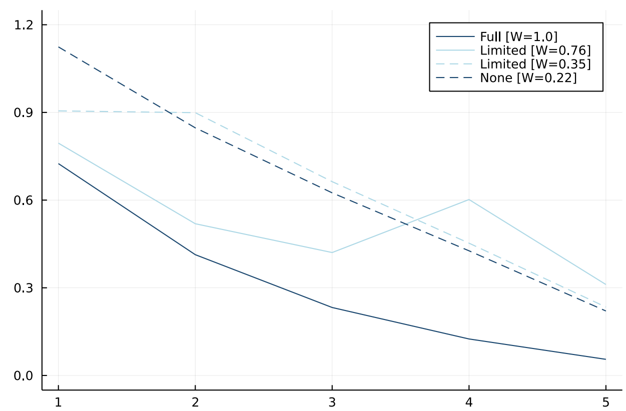
I simulate coastal development and defense over five periods. Figure 6a considers a forward-looking government. Full commitment gives the first best, while no commitment induces moral hazard and over-development in each period. Limited commitment involves under-development during the commitment period, offsetting the over-development that follows. Figure 6b considers a politically myopic government. Limited commitment does less to reduce over-development, as the benefits of commitment are undercut by the failure to internalize future costs. Figure 6c considers relocated demand that reduces coastal residential value by 25%. Moving

Figure 6: New coastal development over time (d_t)

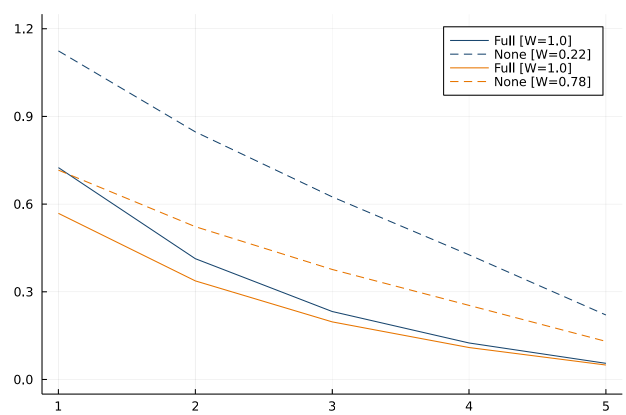
(a) Forward-looking government



(b) Political myopia



(c) Relocating demand



In the first two figures, limited commitment is for one and three periods (dashed and solid, respectively). Social welfare is denoted by "W" and normalized to one under full commitment. In the third figure, orange marks a moved capital that reduces residential value by 25%.

Table 2: Welfare effects

	L	W Baseline	W Relocating demand
Full commitment	5	1.00	1.00
No commitment	0	0.22	0.78
Limited commitment			
Forward looking	3	0.85	0.94
Political myopia	3	0.76	0.92
Limited commitment			
Forward looking	1	0.43	0.82
Political myopia	1	0.35	0.81

I simulate over five periods, with L denoting periods of commitment. For limited commitment, a forward-looking government considers social welfare W until the terminal period, while a politically myopic government ignores future costs. Welfare columns each normalize full-commitment values to one, and relocating demand reduces residential values by 25%.

the political capital from Jakarta might lead to such a reduction, as could other policies like inland investments or migration subsidies. Lower demand reduces developers' gains from exploiting the government, lessening moral hazard and reducing over-development under non-commitment. Appendix D presents the corresponding patterns of government defense.

Table 2 computes welfare effects. The baseline analysis characterizes the commitment problem, normalizing first-best welfare to one. Full commitment achieves the first best. Non-commitment has severe consequences, resulting in only 22% of first-best welfare. Limited commitment leads to large gains. Under a forward-looking government, one-period commitment brings 43% of first-best welfare, and three-period commitment 85%. Political myopia undercuts these gains, but they remain substantial relative to no-commitment outcomes. I then relocate demand and repeat the commitment simulations, again normalizing first-best welfare to one. Relocating demand greatly reduces the commitment problem, raising no-commitment welfare to 78% of first-best welfare and scaling limited-commitment outcomes proportionally.

9 Conclusion

This paper studies adaptation to sea level rise in Jakarta, the second-most populous metropolitan area in the world. I show that adaptation faces major frictions, including over the long run, as government intervention worsens lock-in by creating moral hazard for private developers. Government commitment reduces this friction but is subject to fundamental challenges. Jakarta thus provides an early view into the future for other major coastal cities like Miami, New York, and Shanghai as sea levels continue to rise worldwide.

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APPENDIX

A Theory

Extensions

I consider inland development that does not require flood defense. The typical adaptation narrative is that flood risk prompts a move inland, reestablishing agglomeration forces away from flood zones over the long run. Endogenizing government intervention complicates this narrative by inducing coastal over-defense. The result is significant delay to the move inland, as coastal and inland development are rival. Agglomeration does not take hold inland as long as coastal over-development keeps residents at the coast. Allowing inland development thus increases welfare losses.

To this end, I consider endogenous rents determined in equilibrium. Coastal defense protects against flooding, raising the returns to coastal development. But as development increases at the coast, greater supply places downward pressure on rents. At the same time, a countervailing force is that lower rents encourage individuals and firms to move in, with greater demand placing upward pressure on rents. The quantitative exercise considers these forces in spatial equilibrium by modeling individuals and firms that co-locate across coastal and non-coastal neighborhoods.

Finally, I consider durable defense. In this case, defense investments are largely upfront: if defense is optimal tomorrow, then it is optimal today because it protects development for an additional period. Future defense investment are thus minimal under the baseline assumptions, particularly if defense depreciates slowly. In reality, however, rising sea levels increase flood risk over time and prompt continued investment in defense. Similarly, rising rents and falling costs prompt continued development, as do convex costs that force development to be spread over time. Non-durable defense thus captures the repeated government intervention observed in the richer model, as well as in practice.[23]

Anecdotal evidence

The co-determination of development and defense is also salient in practice. In Jakarta, figure A1 shows examples of interdependence. Developers cite government defense in planning for and marketing private development on the flood-prone coast. At the same time, the government cites private development in planning for and marketing proposed investments in coastal defense.

[23] Non-durable defense has another benefit. Durable defense and two periods lead to a government desire to reduce defense in period two. Period-one defense protects development for two periods, but period-two defense protects for only one period and thus has lower benefits. However, this effect is an artifact of the two-period model and disappears over the infinite horizon. Non-durable

Figure A1: Co-determination of development and defense

(a) Development given defense

(b) Defense given development

Source: PIK2 Sedayu Indo City (via *https://www.sedayuindocitypik2.com/lokasi.html*) and National Capital Integrated Coastal Development Masterplan (2014, page 48). The figures show private development plans given proposed government defense, and government defense plans (at early, hand-drafted conception) given proposed private development.

Table B1: Data sources

Period	Source (description)
1975-2020	Global Human Settlement Layer (building construction, populations)
2015	Visicom (building construction)
2022	99.co (property values)
2015	Brickz.id (Harari and Wong 2019) (property values)
2015	Jakarta Smart City (land values)
2013-2020	Regional Disaster Management Agency (flooding)
1887-1945	Dutch colonial maps (historical land development)

Similar dynamics arise in the United States. In New Orleans, the National Flood Insurance Program (NFIP) has enabled continued development in flood-prone neighborhoods, such as the Lower Ninth Ward. In North Carolina, increased coastal development led business groups to lobby for House Bill 819, which restricts state agencies in applying sea level rise projections to policy. In Florida, developers lobbied for Urban Development Boundary zoning expansions to allow construction in hurricane-prone areas, and the state legislature dismantled the Department for Community Affairs, which managed long-term development risk with initiative like the Flood Mitigation Assistance program. At the national level, NFIP Risk Rating 2.0 adjusted insurance pricing to better reflect risk, but bipartisan resistance delayed implementation. Furthermore, the US Army Corps of Engineers focuses levee spending where economic exposure is high via its Levee Safety Action Classification system.

B Data

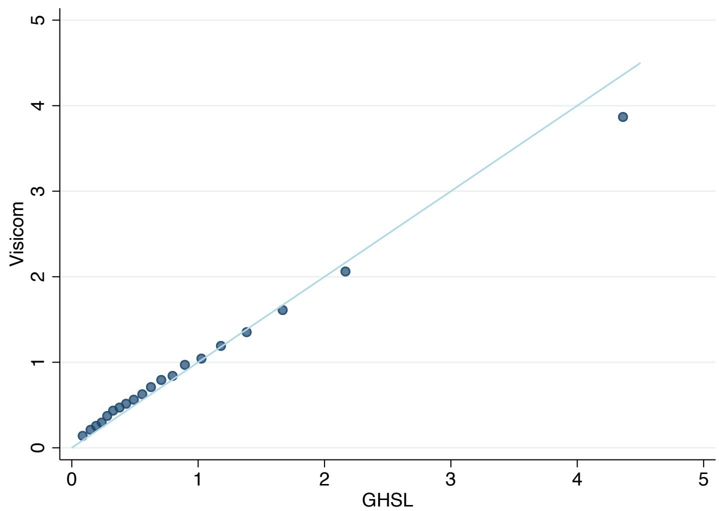
Table B1 lists data sources. This section details data construction and validation.

Building construction

These data come from the Global Human Settlement Layer, with measurements at the 100m pixel level. Jakarta consists of 65,260 such pixels. For building construction, 1,900 pixels feature an increase in measured built-up volume between 2015 and 2020. I verify these data with 2015 data from Visicom, a company that produces satellite-derived 3D maps that capture building heights at the 1m pixel level. These maps rely on light detection and ranging (lidar) data, which satellites collect by emitting pulsed laser beams and measuring reflection times. Beams that reflect quickly imply taller building heights, with measurements accurate to the meter. When aggregated to the tract level, the correlation between Global Human Settlement Layer and

defense eliminates it even in the two-period case.

Figure B1: Building volumes (1M m^3), GHSL vs. Visicom



Source: Global Human Settlement Layer and Visicom. Each observation of the binned scatterplot measures 2015 built-up volume at the tract level. I plot the 45° line in light blue.

Visicom measures is 0.90 for built-up surface and 0.92 for built-up volume. Figure B1 shows the comparison visually.

Property values

I collect property values in four steps. First, I scrape data on property listings in October 2022 from 99.co Indonesia (*www.99.co/id*), a major real estate website. I focus on properties for sale, with listings covering both residential and non-residential properties in Jakarta. Residential properties include apartments and homes, and non-residential properties include shops and offices. Listings contain prices, floor spaces, land areas, addresses, and descriptions.

Second, I geolocate listings with the Google Maps API. As inputs, I supply property addresses, types, and districts. Property addresses include street names and sometimes street numbers. I identify street names with the keyword *jalan* where possible. For apartments, I also include apartment complex names given keyword *apartemen*. As outputs, I obtain formatted addresses with geographic coordinates and return types. I keep the following return types: street addresses, routes, establishments, points of interest, premises, and sub-premises. Routes are entire streets and thus require additional processing to geocode. I compute street lengths from geometric bounds, drop long streets, and geocode the short ones that remain by centroid. A cutoff length of 1 km avoids dropping data excessively while maintaining accuracy at the tract level. Table B2 shows the high rate of success in geocoding.

Third, I construct property values at the tract level. I compute prices per square

Table B2: Geocoding property listings

Type	All	Apartment	Home	Shop	Office
Geocoded proportion	65.5%	84.0%	52.6%	56.0%	39.8%
Geocoded observations	56,222	29,733	17,182	7,786	1,521

Property listings for sale come from 99.co, and geocoding is with the Google Maps API.

meter by dividing prices by floor space, dropping the 1% of listings without information on prices or building areas. I collapse listings with identical addresses – primarily apartment listings within complexes – into single observations by taking means. I then aggregate to the tract level as follows. For the 70% of tracts with more than five observations, I take the mean. For the 30% of tracts with less than five observations, I compute an inverse-distance-weighted mean of nearby observations.[24] I thus obtain property values for 2022.

Fourth, I backcast the 2022 values to 2015. I obtain data on 2015 property transactions from Brickz (*www.brickz.id*), as scraped and kindly shared by Harari and Wong (2019). The 2015 data contain 6,929 observations that I use to compute 2015-2022 adjustment factors by district. I do so by computing district means in 2015 and 2022, reweighing 2022 values to match the property type composition of the 2015 data. The resulting adjustment factors capture price changes over time, as well as differences between transacted and listed prices. I then apply the adjustment factors to the 2022 data to obtain 2015 values. Relying directly on the 2015 values would be more straightforward, but the relatively small number of geocoded observations – around half of the 6,929 transactions – complicates measurement at the tract level.

Historical land development

I construct a panel of historical land development by digitizing maps of Batavia from the Dutch colonial era. These maps come from the digital collections of the Leiden University Libraries. Table B3 lists years and sources. I select eight maps based on ease of digitization and a desire for consistent coverage throughout the study period, but the table lists all available maps. I georeference and digitize the maps, then overlay them to form a panel. These data capture the extensive margin of built-up land development, but not the intensive margins of density or height.

I georeference each map by overlaying it onto an OpenStreetMap base layer. I do so by selecting and matching five ground control points, as shown in figure B2. I select these points to prioritize accuracy in the vicinity of the National Monument and

[24] For the inverse distance weighting, I use a weighting power of two, a smoothing parameter of zero, a search circle radius of one kilometer, a maximum of twenty observations, and a minimum of five observations. I include observations from the periphery of Jakarta.

Table B3: Dutch colonial maps

Year	Source
1887	Visser & Co. (link)
1897	Topographisch Bureau (link)
1904	Seyffardt's Boekhandel (link)
1910	Official Tourist Bureau (link)
1920	Topografische Dienst (link)
1930	Official Tourist Bureau (link)
1937	G. Kolff & Co. (link)
1945	AFNEI Headquarters Survey Department (link)

Source: Leiden University Library Digital Collections. Maps are also available for 1890 (link), 1905 (link), 1914 (link), 1938 (link), and 1942 (link).

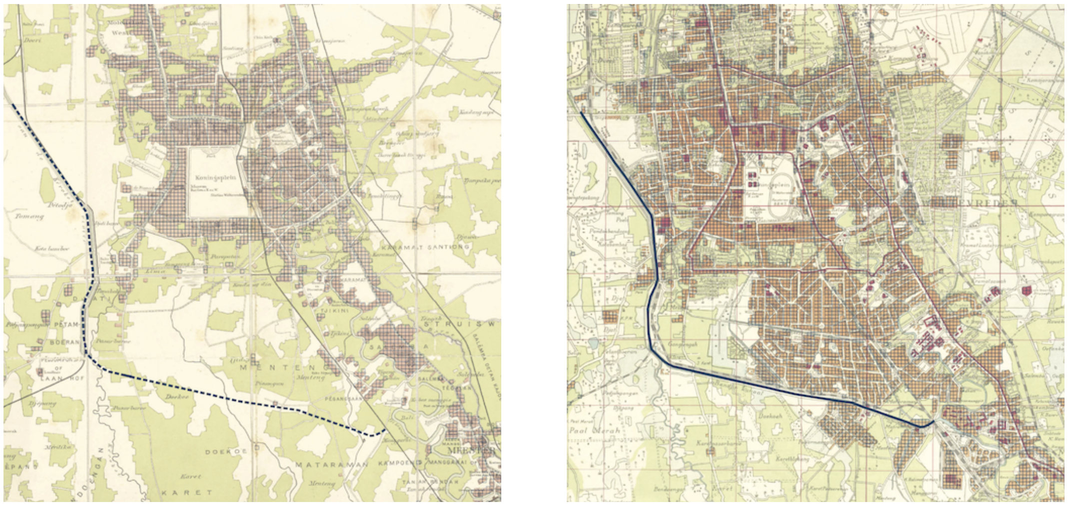
Figure B2: Ground control points for georeferencing

(a) Pre-1918 maps (b) Post-1918 maps

Red stars mark the five ground control points used for georeferencing.

Figure B3: Land development and the West Flood Canal

(a) Before (1904) (b) After (1945)



Red shading denotes developed lands, and square boxes mark 50m grid cells that are coded as developed. I mark the West Flood Canal with a black curve – dotted in 1904 before its construction in 1918, and solid in 1945 after its construction.

the West Flood Canal, with a modified set of points before the canal is constructed. I implement the overlay with first-order polynomial (affine) transformation and nearest-neighbor resampling. This affine transformation preserves the collinearity of points by applying only rotation, scaling, and translation, avoiding image distortions but ruling out the exact matching of more than two control points.

I digitize each map with unsupervised machine learning. In each map, red shading denotes built-up areas, while green and write denote undeveloped lands. I divide maps into 50m grid cells, then I take the modal R, G, and B values across pixels in each cell to obtain one RGB code per cell. I apply a k-means clustering algorithm on these RGB codes to group cells with similar colors. I choose k to obtain no more than one grouping of red cells, and I code these cells as built-up. This approach reduces noise in the image files, which contain red in many different shades. The 1910 map marks built-up areas with red dots instead of shading, and so I apply shading manually then digitize it as above. Figure B3 overlays the image inputs and the digitization outputs, which together illustrate the accuracy of this procedure.

I then ask whether the construction of the West Flood Canal in 1918 led to increased land development in protected areas. I leverage a spatial discontinuity in flooding at the boundary of the canal, which protects areas to its north but not to its south. I plot the discontinuity in land development around the boundary in the main text, alongside the lack of a discontinuity before the canal's opening. In this analysis and what follows, I aggregate the historical land development data to the

Table B4: Land development at the canal boundary by year

	300m bandwidth	400m bandwidth	500m bandwidth	600m bandwidth
North of canal × 1887	-0.06	-0.07	-0.09*	-0.11**
	(0.07)	(0.06)	(0.06)	(0.05)
North of canal × 1897	-0.03	-0.03	-0.00	-0.02
	(0.07)	(0.06)	(0.06)	(0.06)
North of canal × 1904	-0.06	-0.08	-0.09	-0.09
	(0.07)	(0.06)	(0.06)	(0.05)
North of canal × 1920	0.15*	0.23***	0.31***	0.32***
	(0.09)	(0.08)	(0.07)	(0.07)
North of canal × 1930	0.41***	0.41***	0.40***	0.46***
	(0.11)	(0.09)	(0.08)	(0.08)
North of canal × 1937	0.78***	0.76***	0.75***	0.76***
	(0.10)	(0.09)	(0.08)	(0.08)
North of canal × 1945	0.77***	0.76***	0.74***	0.72***
	(0.10)	(0.08)	(0.08)	(0.07)
Tract FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3792	5072	6320	7568

Data on historical land development come from Dutch colonial maps. The West Flood Canal was completed in 1918 and protected neighborhoods to its north, but not to its south. The dependent variable is land development, and each observation is a 100m grid cell. The optimal bandwidth is 500m. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

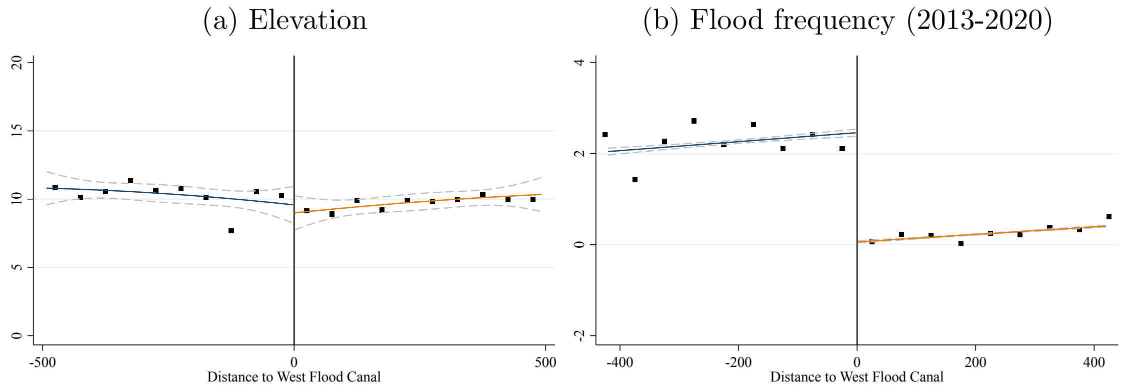
100m cell level by counting the number of developed 50m cells within each 100m cell. Misalignment across maps can cause measurements at the 50m cell level to alternate spuriously between developed and undeveloped because of slight differences in how maps are drawn. Aggregation alleviates this concern without the complexity of harmonizing data across years. Year fixed effects in the pooled analysis further account for systematic differences across maps.

Table B4 draws on data from the full panel to measure the discontinuity in each available year. For cell c and year t, the specification is

$$Y_{ct} = \alpha + \sum_{t'} \beta_{t'} N_c \mathbb{1}[t' = t] + \delta_c + \delta_t + \varepsilon_{ct}$$

for land development Y_{ct}, dummy N_c for being on the protected north of the canal, and year fixed effect δ_t. I compute an optimal bandwidth of 500m, and I restrict attention to cells within this distance from the boundary. I also show robustness

Figure B4: Validating the spatial regression discontinuity design



Data on historical land development come from Dutch colonial maps. The West Flood Canal was completed in 1918 and protected neighborhoods to its north (positive distances), but not to its south (negative distances). Each observation is a 100m grid cell. The x-axis measures distance to the West Flood Canal in meters, and 500m is the optimal bandwidth.

to this choice. The coefficients of interest are the β terms by year. Cell and year fixed effects account for permanent, cell-specific determinants of land development as well as transitory, common ones. The table shows insignificant effects and thus smoothness across the boundary in all pre-canal years. The discontinuity in land development emerges only after the canal opens in 1918, and it grows in subsequent years. Figure B4 provides further validation checks, showing that elevation is smooth across the boundary and that the canal indeed offers flood protection to its north.

A similar pattern holds in the modern cross-section. Lower flood risk is associated with higher land values and more building construction in 2015. Table B5 presents these results with cross-tract regressions that control for unobservables at the district, sub-district, and neighborhood levels. Increased flood protection can therefore prompt increased construction in areas facing long-term flood risk, as it does in the historical data. The advantage of the modern data is that they capture real estate prices as a mechanism for this relationship, as well as development on the intensive margin.

C Estimation

Euler conditional choice probabilities

The Euler approach compares two sequences of actions: $(d^*_{kt}, 0)$ and $(0, d^*_{kt})$. The first develops d^*_{kt} today and zero tomorrow, while the second develops zero today and d^*_{kt} tomorrow. Intuitively, developing tomorrow reduces upfront costs given discounting, but it also delays the arrival of rental revenue. Choice-specific conditional value

Table B5: Flood risk, land values, and building construction

(a) Land value ($\$/\text{m}^2$)

Flood risk (m/yr)	-2.31***	-1.29***	-0.59**	-0.93***
	(3.00)	(3.12)	(2.15)	(2.78)
District FE		x		
Sub-district FE			x	
Neighborhood FE				x
Observations	2,722	2,722	2,722	2,722

(b) Building construction (m^3)

Land value ($\$/\text{m}^2$)	0.21***	0.27***	0.37***	0.30***
	(0.03)	(0.03)	(0.05)	(0.05)
District FE		x		
Sub-district FE			x	
Neighborhood FE				x
Observations	2,722	2,722	2,722	2,722

Each observation is a tract, and each column a regression. Flood risk is realized flooding from 2013 to 2020, land values are from the Jakarta Smart City initiative for 2015, and building construction is from the Global Human Settlement Layer for 2015. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

functions are

$$
\begin{aligned}
v_k^1(w_t) &= -c_{kt}(d_{kt}^*) + \beta \mathbb{E}_{kt}[r_k(w_{t+1})(D_{kt} + d_{kt}^*) + \beta V_k(w_{t+2}) \\
&\quad - \ln\big(1 - p_{kt+1}^{\text{dev}}\big) \mid d_{kt}^*, 0], \qquad (11a)\\
v_k^0(w_t) &= \beta \mathbb{E}_{kt}[r_k(w_{t+1}) D_{kt} - c_{kt+1}(d_{kt}^*) + \beta V_k(w_{t+2}) \qquad (11b)\\
&\quad - \ln p_{kt+1}^{\text{dev}} + \frac{1}{2} c_{kt}''(d_{kt}^*)(d_{kt+1}^* - d_{kt}^*)^2 \mid 0, d_{kt}^*].
\end{aligned}
$$

The first and third lines impose the actions of interest to equations 7. These actions may depart from the optimal actions implied by the choice-specific conditional value functions, and so correction terms in the second and fourth lines account for this potential suboptimality. These correction terms are derived from the following.

$$
\begin{aligned}
V_k(w_t) - r_k(w_t) D_{kt} &= v_k^1(w_t) - \ln p_{kt}^{\text{dev}} = v_k^0(w_t) - \ln\big(1 - p_{kt}^{\text{dev}}\big),\\
v_k^1(d_{kt}^*, w_t) - v_k^1(d_{kt}, w_t) &= \frac{1}{2} c_{kt}''(d_{kt})(d_{kt}^* - d_{kt})^2
\end{aligned}
$$

The first line is a special case of Arcidiacono and Miller (2011) Lemma 1, and the second line is as derived in Hsiao (2022). Substituting equations 11 into equation 9, which describes the logit inversion, continuation values cancel given finite dependence with $\mathbb{E}_{kt}[V_k(w_{t+2}) \,|\, d^*_{kt}, 0] = \mathbb{E}_{kt}[V_k(w_{t+2}) \,|\, 0, d^*_{kt}]$. For $\Delta X_{kt} = X_{kt} - \beta X_{kt+1}$,

$$\Delta \ln p^{\text{dev}}_{kt} - \Delta \ln\big(1 - p^{\text{dev}}_{kt}\big) = -\Delta c_{kt}(d^*_{kt}) + \beta r_k(w_{t+1}) d^*_{kt} - \frac{1}{2}\beta\psi(d^*_{kt+1} - d^*_{kt})^2 + \eta_{kt}$$

for expectational errors η_{kt}, which by rational expectations are mean zero and orthogonal to information set $\mathcal{J}_{kt}$. That is, expectations are assumed to be correct on average and to use all available information.

Hydrological model of flooding

I use a hydrological model to capture flood risk for Jakarta. Flooding models fall in two broad categories: physical and data-driven. The first explicitly models physical processes like rainfall, runoff, hydraulics, and flow dynamics, while the second fits historical data with statistical methods like linear regression, Bayesian models, and machine learning. I take the second approach, which has become increasingly popular among hydrologists. Physical models must specify the complex physical processes that contribute to flooding, while machine-learning methods can detect these complexities directly from the data. Mosavi et al. (2018) reviews the machine-learning approach for hydrology, and Jati et al. (2019) offers an example in the Indonesian setting.

As model inputs, I use rainfall, elevation, slope, distances to major rivers, distance to minor rivers, and distance to the coast. Annual rainfall data at a resolution of 4km come from PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) for the years 2015 and 2020. Elevation data at a resolution of 90m come from the Shuttle Radar Topography Mission (SRTM) digital elevation model. I calculate slopes from elevation data using the slope algorithm of the QGIS raster terrain analysis toolkit, which computes slope in degrees as the angle of terrain inclination. I compute river and coastal distances with OpenStreetMap shapefile data, which distinguish major rivers from streams.

As model output, I obtain predicted flood frequency. This flooding includes all sources of flooding – coastal, pluvial, and fluvial – and is net of river water management infrastructure, which I hold fixed in counterfactuals. I train the model and evaluate its performance using monthly data from the Regional Disaster Management Agency on realized flooding from 2013 to 2020. I rasterize these tract-level data to a resolution of 300m for consistency with demand and supply estimation.

I consider a range of models and choose the one with the best fit. Table C1 presents the results. Ensemble methods like random forests, gradient boosting decision trees, and histogram gradient boosting decision trees perform best, as measured by R-squared, mean absolute error, and root mean squared error. As the baseline model, I choose a histogram gradient boosting decision tree with monotonicity constraints on distance to major rivers and elevation. I train this model using the *scikit-*

Table C1: Comparing models

	R^2	MAE	RMSE
Multiple linear regression	0.021	2.472	3.786
Decision tree	0.202	2.099	3.393
Bagging	0.437	1.581	2.867
Random forest	0.482	1.567	2.774
Gradient boosting decision tree	0.496	1.542	2.679
Histogram GBDT	0.496	1.543	2.698
Histogram GBDT with monotonicity	0.499	1.536	2.694

I compute R-squared, mean absolute error (MAE), and root mean squared error (RMSE) with ten-fold cross-validation. Monotonicity constraints apply to distance to major rivers and elevation.

learn package in Python, which yields model parameters of 12 for maximum tree depth, 200 for maximum iterations, and 0.01 for the learning rate. Monotonicity constraints enforce that fluvial flooding is concentrated near rivers and coastal flooding is concentrated in low-lying areas. These constraints help reduce overfitting by imposing physical properties, but without the complexity of a full physical model.

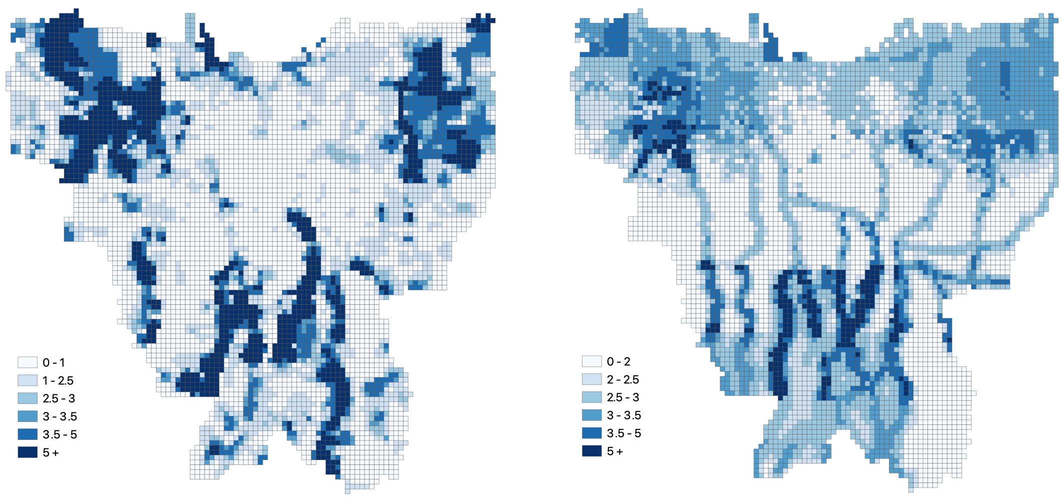
Figure C1 shows visual fit. The model performs reasonably well in capturing the main sources of flood risk in Jakarta. Distance to major rivers and rainfall in upstream watersheds capture fluvial and pluvial flooding historically, while distance to the coast and elevation capture growing coastal flooding. Table C2 summarizes feature importance as another means of evaluating the model. I compute permutation feature importance for individual features by shuffling them – adding random noise to their values – and measuring the resulting declines in model fit. The results are sensible, with distance to major rivers and distance to the coast being of primary importance, and distance to minor rivers and slope being less pivotal.

D Counterfactuals

Figure D1 plots simulated government defense over time. Non-commitment leads to higher defense than under full commitment. Limited commitment prompts initial under-defense relative to the first best, which mitigates future moral hazard, but only when the current government is forward-looking. Otherwise political myopia induces over-defense, even during the commitment period, as costs to future administrations remain uninternalized. Relocating demand lessens the commitment problem.

Figure C1: Model fit (flood frequency)

(a) Observed (b) Predicted



The figures map observed flood frequency, as measured in months per year from 2013 to 2020, against the predictions of a machine learning hydrological model.

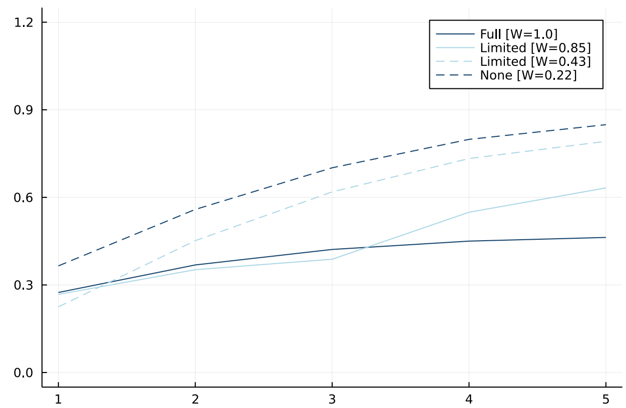
Table C2: Feature importance

Feature	Importance
Distance to major rivers	0.523
Distance to the coast	0.458
Annual rainfall (2020)	0.417
Elevation	0.335
Distance to minor rivers	0.299
Annual rainfall (2015)	0.299
Slope	0.162

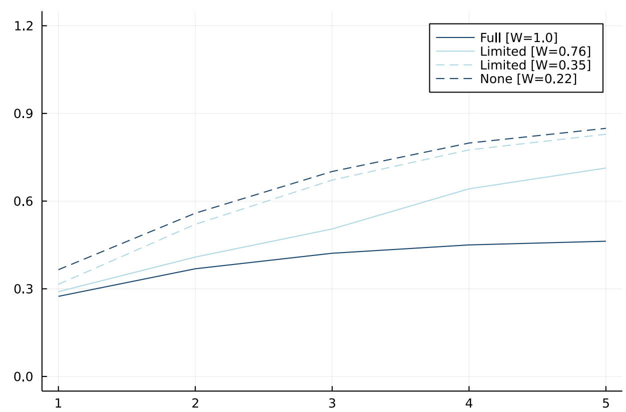
Permutation feature importance quantifies the dependence of model fit on a given feature. The table presents this measure for a histogram gradient boosting decision tree with monotonicity constraints on distance to major rivers and elevation.

Figure D1: Coastal defense over time (g_t)

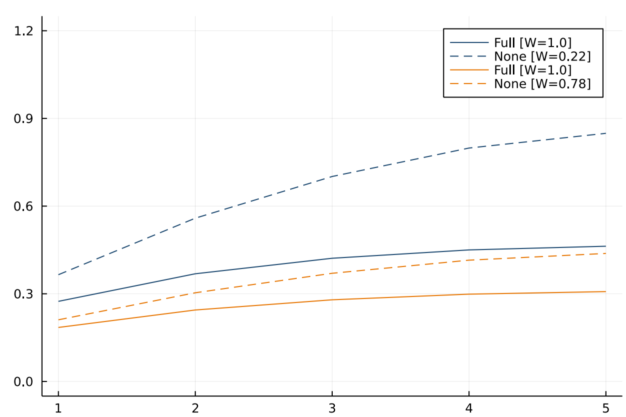
(a) Forward-looking government



(b) Political myopia



(c) Relocating demand



In the first two figures, limited commitment is for one and three periods (dashed and solid, respectively). Social welfare is denoted by "W" and normalized to one under full commitment. In the third figure, orange marks relocated demand that reduces residential value by 25%.