Sea Level Rise and Urban Adaptation in Jakarta

Allan Hsiao

Princeton University

April 18, 2023
(most recent version here)

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 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 32 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 government intervention complicates long-run adaptation by creating moral hazard. The government tends to protect coastal development ex post despite not wanting to ex ante, inducing over-development in anticipation of 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 development responded to historical intervention in Jakarta. The West Flood Canal was completed in 1918 and diverts a major river around city center, protecting areas to its north but not to its south. I measure historical land development by digitizing Dutch colonial maps from 1887 to 1945, and I apply a spatial regression discontinuity design at the canal boundary in the spirit

[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."

of Almond et al. (2009). The north and south are similar before the canal, but the north experienced less flooding and more development after the canal's completion. Intervention induced increased development.

I study how this response creates a commitment problem for 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 flooding in mind. Residential demand is spatial, as individuals make location decisions based on rents, flooding, 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. Equilibrium 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 reads continuation values from data on market prices, in the style of Kalouptsidi (2014), and again addresses the endogeneity of rents with instruments. If markets are efficient, then property prices capture the stream of rents from completed development, and land prices capture the option value of undeveloped land. Prices thus reflect continuation values, inclusive of expectations over future flooding and intervention. Finally, I follow the frontier of the hydrological literature in training a machine-learning model with monthly, tract-level data on flooding from 2013 to 2020. A histogram gradient boosting decision tree fits the data well and offers sensible predictions for how sea wall construction decreases flooding over space.

In simulations, I quantify the effects of commitment on long-run adaptation and social welfare. I consider both forward-looking and politically myopic governments, as well as the impact of reducing coastal demand. I find that non-commitment increases coastal development, slowing adaptation and reducing 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. Reducing coastal demand, including by moving the political capital from Jakarta, lessens both moral hazard and welfare losses under non-commitment. This move also requires commitment, but may be more politically feasible than commitment not to intervene at the coast. Full counterfactuals are in progress.

I highlight implications for policy. First, political economy is crucial. Commitment eliminates moral hazard but is difficult in practice. Indeed, politics often push governments to prioritize short-run gains. I quantify how political forces hinder adaptation and worsen damages from climate change. Second, political constraints may be less binding for policies that encourage rather than punish. Subsidizing inland migration, for example, lessens coastal demand and thus moral hazard, but is less efficient than directly restricting coastal development. Governments should consider politically feasible policy whether or not it achieves the theoretical first best.

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). In particular, Desmet et al. (2021) show that inland migration 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 exacerbates moral hazard, as intervention spurs coastal investment that forces further intervention. The result is severe coastal lock-in at high social cost, in contrast to the smooth inland transition of Desmet et al. (2021). The same force rationalizes the incomplete capitalization of flood risk into property prices (Hino and Burke 2021, Bakkensen and Barrage 2022, Gourevitch et al. 2023) and the persistence of coastal concentration (Vigdor 2008, Kocornik-Mina et al. 2020, Lin et al. 2022), even absent biased beliefs.

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 land use models with data generally available in urban settings, where dynamics are important given the durability of development (Glaeser and Gyourko 2005, Murphy 2018). My approach allows for straightforward estimation, transparent identification, and flexible expectations, as in the Euler conditional choice probability approach of Scott (2013). But unlike the Euler approach, I do so without appealing to finite dependence. My approach thus offers an alternative for when finite dependence is infeasible or requires strong assumptions. 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. 2023).

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.[3] Jakarta's challenges are the world's challenges.

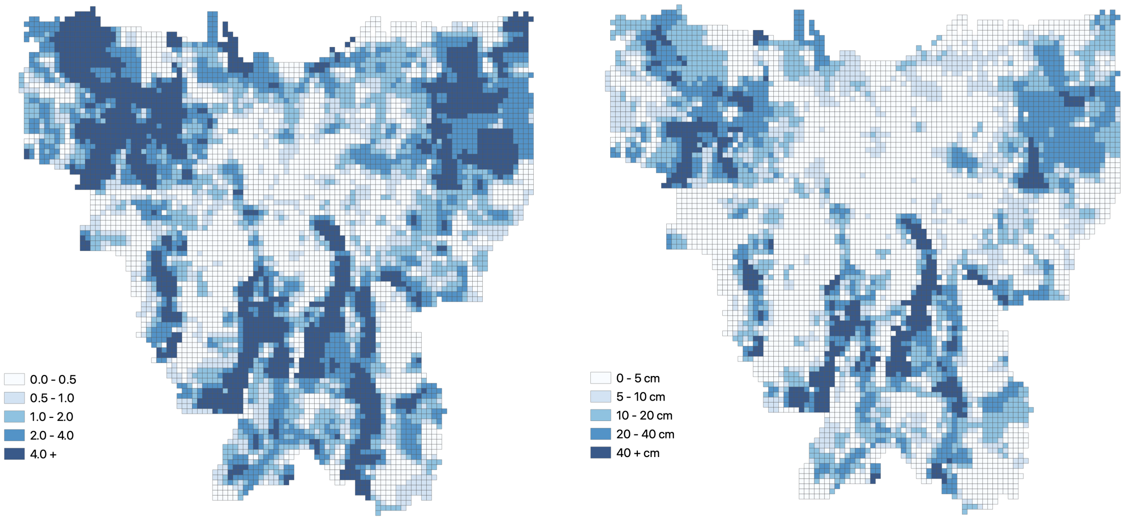
2 Background

Flooding has long plagued Jakarta, which occupies a delta where thirteen rivers meet the ocean. This nexus of waters both nurtures and menaces the city. 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. The key challenge has been fluvial (river) flooding from extreme rainfall, and so historical efforts have focused on river infrastructure

[3] China plans 15,000km of coastline sea wall, Japan has built 400km, and Miami plans 10km. The Northern European Enclosure Dam project proposes dams from France to England and Scotland to Norway. The BIG U project details plans for Lower Manhattan.

Figure 1: Flooding (2013-2020)

(a) Frequency (b) Depth



Source: Regional Disaster Management Agency (*BPBD* via *data.jakarta.go.id*). Frequency is average months per year with flooding, and depth is average monthly flood depth. Each is by 300m cell.

that includes 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 complements a broader system of drains, pumps, reservoirs, and flood gates.

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 5m by 2050, compared to projected sea level rise of 25cm (Andreas et al. 2018, Kulp and Strauss 2019). Groundwater extraction drives subsidence. Piped surface water accounts for only half of total water consumption, with the shortfall met by groundwater extraction that is largely unregistered and unregulated (Taftazani et al. 2022). Water demand continues to rise with a growing population, but surface water reserves remain fixed and undermined by pollution, poor treatment, and limited piping infrastructure (Luo et al. 2019). Efforts to quell subsidence thus face fundamental difficulties.

These existential threats to the nation's capital have prompted two major government initiatives. Stakes are high in this context, as public funds involve forgone investment in areas like education with known aggregate benefits (Hsiao 2023). First, a sea wall has been in discussion since 2011, with costs of up to $40 billion (Garschagen et al. 2018, Colven 2020). Proposals for this "Great Garuda Project" 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 Development Masterplan (NCICD) in 2014, with further revisions in 2016 and the Integrated Flood Safety Plan (IFSP) in 2019.

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 politics generate coastal moral hazard and delay inland adaptation.

3.1 Coastal development and defense

I model flood-prone coastal development and the government investment aimed at defending it. In each period t, development d_t and defense g_t create residential value $r(D_t, G_t)$, which is increasing and concave in $D_t = D_{t-1} + d_t$ and $G_t = G_{t-1} + g_t$. Complementarity $\kappa = \frac{\partial^2 r}{\partial D \partial G} > 0$ captures that development requires defense to protect it, while defense requires development to protect. Durability generates dynamics. Development and defense incur costs $c(d_t)$ and $e(g_t)$, which are increasing and weakly convex.[4] Defense encompasses any intervention that raises residential value, including flood insurance programs, although I focus here on physical infrastructure.[5]

Consider a two-period model. For simplicity, I begin with initial $D_0 = 0$ and

[4] For $r(D, G)$, $\frac{\partial r}{\partial D}, \frac{\partial r}{\partial G} > 0$ and $\frac{\partial^2 r}{\partial D^2}, \frac{\partial^2 r}{\partial G^2} < 0$. Fixing G, $r'(D; G)$ is a downward-sloping demand curve, and $r(D; G)$ is area under the curve for $[0, D]$. Higher G shifts demand upward, subject to diminishing marginal returns to G. For costs, $\frac{dc}{dd}, \frac{de}{dg} > 0$ and $\frac{d^2c}{dd^2}, \frac{d^2e}{dg^2} \geq 0$.

[5] Coastal flooding presents recurring aggregate risk, limiting the role of risk aversion and sharing. Subsidized flood insurance still raises $r(D, G)$ and, like infrastructure, is a coastal transfer.

non-durable $G_t = g_t$, then I relax each. In the first best, the social planner chooses development and defense paths (d_1, d_2) and (g_1, g_2) to maximize social welfare

$$W_1^* = r(d_1, g_1) - c(d_1) - e(g_1) + \beta r(d_1 + d_2, g_2) - \beta c(d_2) - \beta e(g_2).$$

For $r_t'(x) = \frac{\partial}{\partial x} r(D_t, G_t)$, the first order conditions are

$$\begin{aligned} &[d_1^*] \quad r_1'(d_1) + \beta r_2'(d_1) = c'(d_1), \qquad &&[g_1^*] \quad r_1'(g_1) = e'(g_1), \\ &[d_2^*] \quad r_2'(d_2) = c'(d_2), &&[g_2^*] \quad r_2'(g_2) = e'(g_2). \end{aligned} \tag{1}$$

I study how politics give rise to strategic interaction between development and defense. With political myopia, a current government claims credit for the benefits of development, but it ignores the costs of defense for future administrations. It thus encourages development at uninternalized future cost. The current government chooses (d_1, g_1) to maximize W_1^M, then the future government responds with (d_2, g_2) to maximize W_2^M. The latter takes the former as given, with myopic welfare

$$\begin{aligned} W_1^M &= r(d_1, g_1) - c(d_1) - e(g_1) + \beta r(d_1, g_2(d_1)), \\ W_2^M &= r(d_1 + d_2, g_2) - c(d_2) - e(g_2) \end{aligned}$$

for $g_2(d_1, g_1) = g_2(d_1)$ given $G_t = g_t$. The first order conditions are

$$\begin{aligned} &[d_1^M] \quad r_1'(d_1) + \beta r_2'(d_1) + \beta r_2'(g_2) g_2'(d_1) = c'(d_1), \\ &[d_2^M] \quad r_2'(d_2) = c'(d_2), \end{aligned} \tag{2}$$

where conditions ($2g_1^M$, $2g_2^M$) coincide with ($1g_1^*$, $1g_2^*$).

With national financing, a local government encourages development at uninternalized national cost. The local government chooses d_1 to maximize W_1^L, then the national government responds with g_1 to maximize W_1^M.[6] The latter takes the former as given, and each anticipates the same process for (d_2, g_2). Local welfare is

$$\begin{aligned} W_1^L &= r(d_1, g_1(d_1)) - c(d_1) + \beta r(d_1, g_2(d_1)), \\ W_2^L &= r(d_1 + d_2, g_2(d_2)) - c(d_2). \end{aligned}$$

[6] The local government allows national choice of defense because it values national financing, otherwise local financing leads to (d_1^M, g_1^M) with lower local welfare even before added cost $e(g_1^M)$.

The first order conditions are

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

where conditions ($3g_1^L$, $3g_2^L$) coincide with ($1g_1^*$, $1g_2^*$).

Development can also be developer-driven, as articulated in Kydland and Prescott (1977), with equivalent outcomes if developers internalize their impact on government defense. To this end, I consider an association of coastal residents and developers that benefit from defense. This association subsidizes marginal development, which raises defense, and it does so as long as there remain gains to coastal welfare. That is, inframarginal development gains from marginal development, and it passes these gains along with transfers.[7] Coastal welfare coincides with local welfare (W_1^L, W_2^L), and outcomes are given by conditions 3. Indeed, the local government plays the same implicit role when choosing development directly.

3.2 Moral hazard

Moral hazard arises from time inconsistency. Without commitment, static incentives prevail. Defense responds to development, such that $g_1'(d_1)$, $g_2'(d_1)$, $g_2'(d_2) > 0$.[8] Development thus forces defense at uninternalized cost, yielding over-development $d_1^L > d_1^M > d_1^*$. Like typical moral hazard, protection leads to uninternalized risk and excessive risk-taking. Unlike typical moral hazard, risk-taking prompts greater risk protection: defense encourages development, which in turn forces further defense. This feedback amplifies the typical distortion.[9]

Commitment eliminates moral hazard but faces challenges. Fixed defense implies $g_2'(d_1) = g_1'(d_1) = g_2'(d_2) = 0$, such that conditions 1, 2, and 3 coincide. State-

[7] Let inframarginal development be that independent of the influence of development on defense, where $g_s'(d_t)$ for all s, t gives d_t^*. Inframarginal d_t^* then subsidizes marginal $(d_t^L - d_t^*)$.

[8] Differentiating condition $2g_2^M$ with respect to d_1 yields $\kappa[1 + d_2'(d_1)] = [e''(g_2) - r''(g_2)]g_2'(d_1)$ for $\kappa > 0$, $e''(g_2) \geq 0$, and $r''(g_2) < 0$. I claim that $\frac{d}{dd_1}[d_1 + d_2(d_1)] = 1 + d_2'(d_1) > 0$ given $d_2 > 0$. If not, then $\frac{d}{dd_1}[d_1 + d_2(d_1)] \leq 0$. For $d_1 = 0$ and $d_1' = d_2(0)$, where $d_2(0) > 0$ by $d_2 > 0$, it follows that $d_2(0) + d_2(d_2(0)) \leq 0 + d_2(0)$ and thus $d_2(d_2(0)) \leq 0$. Contradiction with $d_2 > 0$ proves the claim. Thus, $g_2'(d_1) > 0$. Differentiating condition $3g_t^L$ with respect to d_t yields $\kappa = [e''(g_t) - r''(g_t)]g_t'(d_t)$ with $\kappa > 0$, $e''(g_t) \geq 0$, and $r''(g_t) < 0$. Thus, $g_t'(d_t) > 0$.

[9] Typically, the principal cannot directly control risk-taking by the agent because of hidden action. Here, development is not hidden. The challenge is time inconsistency.

contingent commitment allows uncertainty. But first, static incentives can be substantial, as even the social planner finds it optimal to defend after development is sunk. Elections, lobbying, and corruption only worsen these incentives. Second, commitment must always hold, as over-development persists if $g_s'(d_t) > 0$ for any $s \geq t$. Third, non-commitment compounds across periods, as development is persistent and forward-looking. Over-development d_1 raises g_2 and in turn d_2, just as d_2 raises g_2 and in turn d_1. Commitment is difficult, even for one period and especially for many.

Moral hazard thus generates coastal lock-in at high social cost. Even ignoring land subsidence, sea level rise projections reach 1m in 2100, 3m in 2200, and 10m in 2300 for RCP8.5 (Kopp et al. 2014, van de Wal et al. 2022). Gradual inland retreat, as Desmet et al. (2021) envision, calls for declining coastal development given growing long-run risk. But reality is one of coastal persistence and even intensification (Kocornik-Mina et al. 2020, Lin et al. 2022). Moral hazard offers an explanation, as defense displaces adaptation in the form of retreat. The consequence is continued spending on defense and large damages should it fail.

Moral hazard is lessened if development internalizes the costs of defense. Developers may face regulation, but they have strong incentives to lobby against it. Governments are likely receptive. While current governments might weigh the future, politics are present-biased in many settings. And while local governments might rely on local financing, cost-sharing is common in practice. National ministries have led sea wall planning for Jakarta and contributed funding for initial construction.[10] Even with local financing, inland residents help fund coastal defense despite not benefiting directly. Moral hazard also requires interior solutions, as there is little scope for over-defense if defense guarantees safety or is infeasible. But sea walls cannot guarantee safety, as storm surges generate overtopping risk. And international aid bolsters capacity to defend. Indeed, sea wall plans for Jakarta draw on Dutch expertise.

Existing development $D_0 > 0$ worsens losses from moral hazard. For welfare loss $\Delta W_1^M = W_1^* - W_1^M$ and $\Delta W_1^L = W_1^* - W_1^L$, differentiating with respect to D_0 gives

$$\frac{d\Delta W_1^M}{dD_0} = \beta r_2'(g_2) g_2'(D_0), \qquad \frac{d\Delta W_1^L}{dD_0} = r_1'(g_1) g_1'(D_0) + 2\beta r_2'(g_2) g_2'(D_0).$$

[10] E.g., national ministries of public works (*PUPR*) and development planning (*Bappenas*). Beyond Jakarta, New York City sea wall plans propose 65% federal and 35% state funding (USACE 2022).

Each is positive given $g_1'(D_0), g_2'(D_0) > 0$, which holds as $g_1'(d_1), g_2'(d_1) > 0$ does previously. Existing development raises the returns to forcing defense at uninternalized cost and thus exacerbates moral hazard. Durable defense $G_t = G_{t-1} + g_t$ can strengthen this effect, as lasting protection again raises the returns to forcing defense. But it may also be more costly and thus more difficult to force.[11]

4 Empirics

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

4.1 Framework

The theory frames the empirical analysis, which constructs analogues for components $r(d, g)$, $c(d)$, and $e(g)$ of social welfare. For development d and defense g, I rewrite $r(d, g)$ as $r(d, f(g))$ given the impact of defense on flooding $f(g)$. I estimate a spatial model of residential demand to obtain $r(d, f(g))$, and I use a hydrological model to describe $f(g)$. I estimate a dynamic model of developer supply to obtain costs $c(d)$ of development, with engineering estimates for costs $e(g)$ of defense. Sections 5 and 6 model residential demand and development supply, which characterize how flooding affects urban development in equilibrium. Section 7 describes the benefits and costs of government intervention.

4.2 Data

I compile high-resolution spatial data on building construction, populations, property prices, land prices, and flooding across Jakarta. The city is divided into

[11] I recompute welfare losses with durable defense. For $r_1'(g_1), r_2'(g_2) > 0$,

$$\frac{d\Delta \tilde{W}_1^M}{dD_0} = 2\beta r_2'(g_2)\tilde{g}_2'(D_0), \quad \frac{d\Delta \tilde{W}_1^L}{dD_0} = [r_1'(g_1) + \beta r_2'(g_2)]\tilde{g}_1'(D_0) + 3\beta r_2'(g_2)\tilde{g}_2'(D_0).$$

Lasting protection strengthens these effects for $\tilde{g}_1'(D_0) = g_1'(D_0)$ and $\tilde{g}_2'(D_0) = g_2'(D_0)$. But costly durability $\tilde{e}(g_t) > e(g_t)$ can weaken these effects through $\tilde{g}_1'(D_0) < g_1'(D_0)$ and $\tilde{g}_2'(D_0) < g_2'(D_0)$. Even fixing costs, $\tilde{g}_2'(D_0) < g_2'(D_0)$ is unambiguous because D_0 raises durable g_1 that undercuts the need for added g_2. And $\tilde{g}_1'(D_0) < g_1'(D_0)$ is possible because durable g_1 displaces g_2. This displacement is costly given uninternalized $e(g_2)$ and thus discourages g_1. But $\tilde{g}_1'(D_0) > g_1'(D_0)$ remains possible because lasting protection has high returns and thus encourages g_1.

five districts (*kota*), 44 sub-districts (*kecamatan*), 267 neighborhoods (*kelurahan*), and 2,722 tracts (*rukun warga*), with each tract containing around 4,000 people. I compile data by 300m cell, or roughly three times finer than tract level. I focus on Jakarta proper, but the empirical analysis will allow for movement across the broader metropolitan area. I exclude the islands of *Kepulauan Seribu* district. Figure 2 illustrates the data, and appendix A provides additional detail.

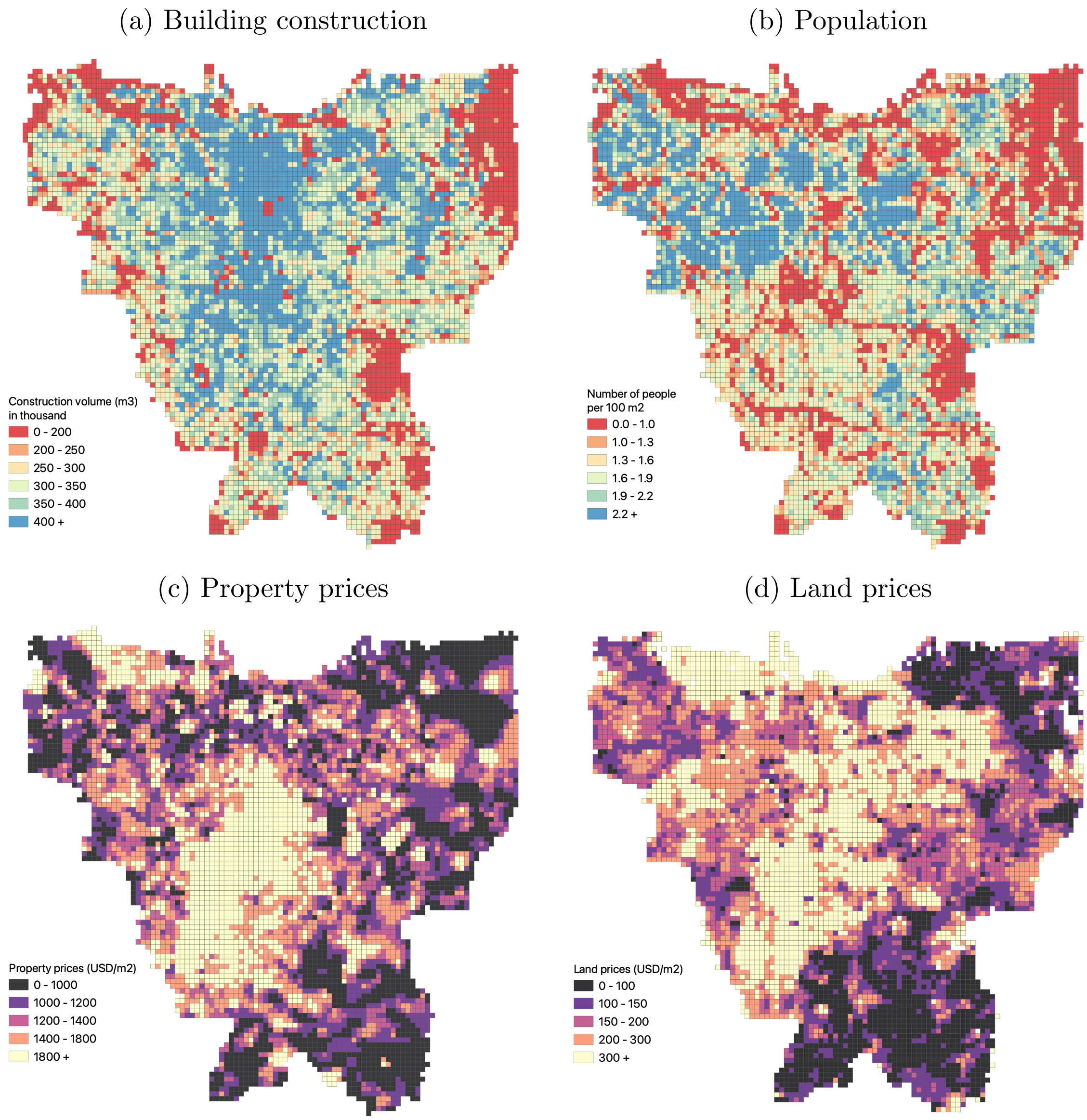
The Global Human Settlement Layer measures building construction and populations across Jakarta (GHSL 2022). It does so by 100m cell every five years from 1975 to 2020, and I aggregate to the 300m cell level. The construction data record built-up surface areas and volumes, separating residential from 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.

I construct property prices for 2015 with data on 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 successfully geocode 56,222 listings with prices and floor spaces for October 2022. I compute prices per square meter of floor space, and I aggregate to the 300m cell level. From brickz.id, I obtain 6,929 property transactions for 2015. I use these data to backcast the 2022 prices and to adjust for differences between listed and transacted prices. I thus obtain transacted property prices for 2015, where property prices combine building and land values.

Land prices 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 prices at a granular level, drawing on administrative data from transactions, market data from brokers and online platforms, and property characteristics from field visits.[12] The data include 20,892 observations at the sub-block level, with

[12] In principle, the city government also computed property prices in the process of computing land prices. I construct property prices myself because these official prices are not public.

Figure 2: Data (2015)



Building construction and populations come from the Global Human Settlement Layer. I construct property prices with transactions and listings data from 99.co and brickz.id. Land prices come from the Smart City initiative of the Jakarta city government. Each figure displays data by 300m cell.

land prices measured as prices per square meter. I aggregate to the 300m cell level. Harari and Wong (2019) describe these data in further detail and take additional steps to verify their quality, including in informal areas. Moreover, the use of these values for tax collection gives them official weight.

Flooding data from 2013 to 2020 come from the Regional Disaster Management Agency. For each month, I observe the tracts that experienced flooding, the depth and duration of flooding, and the number of people affected. I downscale these data to the 300m cell level, and I compute measures of flood frequency and depth. I do so by cell as follows. For flood frequency, I count the number of months each year with flooding, then I average across years. For flood depth, I measure monthly flood depths, then I average across months. Figure 1 maps these frequencies and depths.

I also measure ruggedness and residential amenities with city government data (Jakarta 2022). Ruggedness is the topographic ruggedness index (Riley et al. 1999), and I use digital elevation model data at the 30m level to compute the mean difference in elevation between a cell and its surrounding cells. Residential amenities is an index variable that measures proximity to schools, healthcare clinics, and passenger railway stations. I compute Euclidean distances to the closest point in each category, sum with equal weighting, and take the negative to reflect proximity. Ruggedness provides a supply shifter in estimating demand, and residential amenities provide a demand shifter in estimating supply.

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 1945 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.

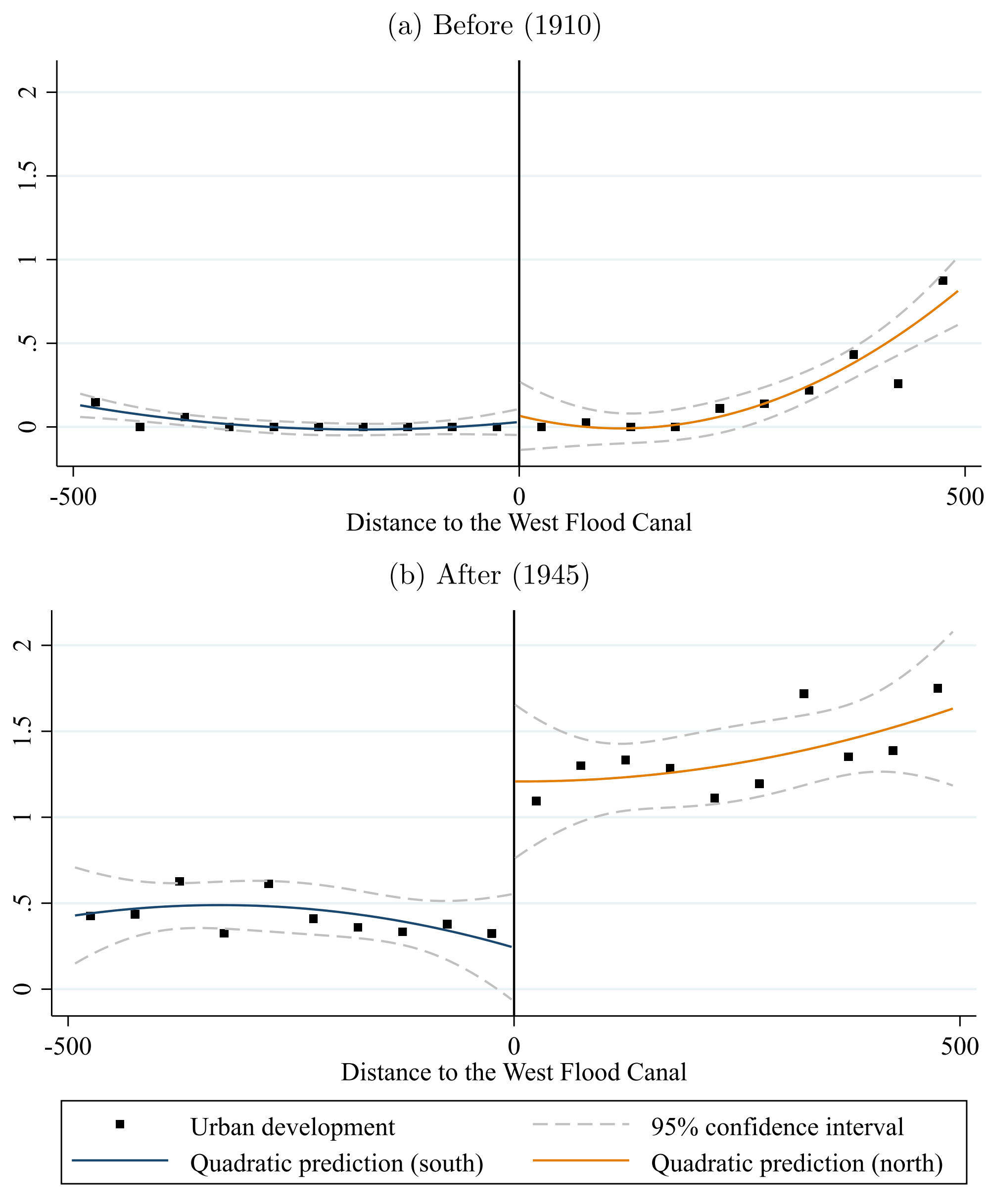
The West Flood Canal diverts floodwaters that flow from the higher-elevation south to the lower-elevation north, protecting neighborhoods north of the canal but not those south of the canal. I leverage this spatial discontinuity to study how land development responds to flood protection, in the spirit of Almond et al. (2009).[13] I restrict attention to cells in the vicinity of the canal, and I plot land development relative to distance to the canal. Figure 3 shows the results: land development jumps at the boundary after the opening of the canal, but not before, as development responds positively to increased flood protection. Appendix A shows regression estimates by year, and it documents decreased flooding north of the boundary, smoothness in elevation across the boundary, and smoothness in land development across the boundary throughout the pre-canal period. Thus, defense encouraged development in places that remain at risk of flooding today. And this additional development raises the stakes for the current sea wall.

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, flooding 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 10km stretch of canal that I study. Finally, the canal may facilitate other forms of government intervention by establishing clear boundaries for favored neighborhoods.[14] Such effects remain consistent with the theory, which only requires that government intervention increase residential value. Absent exhaustive data on non-flood intervention, the empirical model focuses on flooding and abstracts from this dimension. Adding it would worsen moral hazard.

[13] 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 in China. Northern cities receive free coal for winter heating, while southern cities do not.

[14] The prime example of such favoritism is the once-European neighborhood of Menteng, which canal construction explicitly sought to protect. While I do see increased land development in Menteng, I see the same in other northern neighborhoods as well.

Figure 3: Land development and the West Flood Canal



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 cell. The x-axis measures distance to the West Flood Canal in meters, and 500m is the optimal bandwidth.

5 Demand

Residents determine the demand for development, choosing locations with flooding in mind. Estimation matches changes in populations.

5.1 Model

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

$$U_{ijk} = \underbrace{\alpha r_k + \phi f_k + x_k \gamma + \varepsilon_k}_{\delta_k} + \tau m_{jk} + \epsilon_{ijk} \tag{4}$$

for rent r_k, flooding f_k, observed characteristics x_k, unobserved amenity ε_k, migration distance m_{jk}, logit shock ϵ_{ijk}, and destination-specific utility δ_k. Residents seek low rents, low flooding, high amenities, and short distances. Observed x_k include district fixed effects that help capture unobserved heterogeneity. Distance introduces spatial dependence. Residential demand sums over origins given populations n_j and choice probabilities p^{res}_{jk}. Development demanded in each location is thus

$$D^{\text{res}}_k = \sum_j n_j p^{\text{res}}_{jk} \varphi, \quad p^{\text{res}}_{jk} = \frac{\exp(\delta_k - \tau m_{jk})}{\sum_{\hat{k}} \exp(\delta_{\hat{k}} - \tau m_{j\hat{k}})} \tag{5}$$

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, and I address price endogeneity by instrumenting for rents with ruggedness as a cost shifter. I focus on residential choice in the core of Jakarta, with migration to the periphery as the outside option. Total metropolitan population combines core and periphery, and it evolves exogenously. I take rents to be mortgage payments on observed property prices.

Estimation follows Berry (1994) and Berry et al. (1995), except that I integrate over origins instead of over a broader set of demographics. I thus avoid the need to measure bilateral migration flows, which is often difficult in granular settings. I estimate $\theta = (\theta_1, \theta_2)$ for $\theta_1 = (\alpha, \phi, \gamma)$ and $\theta_2 = \tau$. First, fixing θ_2, I match observed and model-implied populations by computing $\delta = \{\delta_k\}$ by contraction mapping. Suppressing dependence on data (n, m), equation 5 implies destination populations

$$n_k = \frac{\lambda}{\varphi} D_k^{\text{res}}(\delta, \theta_2),$$

where computing the right-hand side requires integrating over origin populations n_j. I read destination populations from the 2020 data and origin populations from the 2015 data. Uniform population growth rate $\lambda = (\sum_k n_k^{2020})/(\sum_j n_j^{2015})$ augments 2015 populations, such that origin and destination populations balance. Second, I regress $\hat{\delta}$ on data (r, f, x) to obtain estimates $\hat{\theta}_1$ and residuals $\hat{\varepsilon}$.

$$\varepsilon_k = \delta_k - \alpha r_k - \phi f_k - x_k \gamma$$

Third, I compute the GMM objective function with instruments Z, weighting matrix W, and sample analog $g(\varepsilon(\theta)) = \sum_k Z_k \varepsilon_k(\theta)$ of moment condition $\mathbb{E}[Z\varepsilon(\theta)] = 0$.

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

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 demand estimates, defining locations as 300m cells. I address rent endogeneity by instrumenting with ruggedness as a supply shifter, where ruggedness raises rents with a large F-statistic in the first stage. I find that demand is decreasing in rents and in flooding. The flooding coefficient captures the welfare benefits of decreasing flooding with a sea wall, and the rent coefficient monetizes these benefits. Demand is increasing in residential amenities, as measured by an index

Table 1: Residential demand estimates

	IV		First stage		
	Estimate	SE	Estimate	SE	Mean
Rents (USD/m^2/year)	-0.032***	(0.004)			144
Ruggedness (index)			12.20***	(1.176)	1.43
Flooding (m/month)	-0.490***	(0.097)	-15.53***	(2.485)	0.15
Residential amenities (km)	0.110***	(0.018)	1.540***	(0.469)	2.91
District FE	x		x		
Observations	5,780		5,780		
F-statistic			108		

Each observation is a 300m cell. IV estimation matches population shares, and the first stage is a regression with rents as the dependent variable. Rents are yearly mortgage payments, which I compute from property prices with a discount factor of 0.9. Flooding is as observed from 2013 to 2020. Residential amenities is an index variable that measures proximity to schools, clinics, and passenger rail stations. By 2020 rates, 1M IDR = 70 USD. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of proximity to schools, clinics, and passenger rail stations. I take these observed amenities as exogenous, but future work can apply an optimal placement instrument given potential correlation with unobserved amenities. Counterfactuals will consider the impact of shifting amenities as populations move inland.

I consider magnitudes by comparing coefficients. The rent and flooding coefficients suggest that mean flood levels require a \$2.30 decrease in yearly rents per square meter as compensation variation. Annual construction of 7M square meters of floor space from 1999 to 2013 (BPS 2022), combined with a 5% depreciation rate, suggests 140M square meters of total floor space. Multiplying this total by \$2.30 implies yearly damages of \$320M, consistent with \$300M in accounting damages estimated by Budiyono et al. (2015). Flooding has a standard deviation of 0.26 meters per month. Considering variation within the data, increasing flooding by one and two standard deviations implies further yearly damages of \$560M and \$1.1B. Considering variation beyond the data, flooding at four standard deviations corresponds to one-meter inundation, as is well within the range of projected scenarios for sea level rise by 2100 (IPCC 2019). This level of flooding implies yearly damages of \$2.2B and total damages of \$22B (at 10% discounting).

One 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 quite 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 remain sensitive to even 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. Perfect competition among atomistic developers – as I assume in the supply model to follow – will be consistent with such behavior.

Another concern is that flooding may be correlated with unobserved amenities. On one hand, flood zones may enjoy positive amenities. If coastal proximity bundles increased flooding and ocean views, then it attenuates effects of flooding on residential demand. This bias understates the moral hazard problem. But controlling for coastal distance reveals a small, positive effect on demand, such that coastal amenities seem not to weigh heavily. On the other hand, flood zones may suffer negative amenities. If flooding impedes public and private investment, then it worsens conditions beyond its direct consequences. But such effects are simply part of flood damages. Indeed, the estimate flood coefficient produces reasonable valuations of yearly flood damages, as computed above. Another approach is to focus on discontinuities in flood risk maps (Bakkensen and Ma 2020), but I rely on observed flooding that varies smoothly over space rather than flood risk measures from government maps.

This focus on flooding rather than flood risk mitigates bias from misperception of risk. Risk is challenging to assess, even for experts, and disentangling perceptions from preferences is difficult in general. I isolate preferences by considering how residents respond to eight years of observed flooding history. In this sense, I infer the welfare impacts of future flooding from residents' reactions to past flooding. The implicit assumption that the past flooding, which is largely pluvial and fluvial, is informative of future coastal flooding. Indeed, flooding is flooding. Even so, the nature of climate change makes some extrapolation unavoidable, as sea level rise brings future flooding at unprecedented levels. And while past flooding does capture tail risk, including 30- and 50-year floods in 2013 and 2020, it does not capture permanent inundation. If the past is mild relative to the future, then my demand estimates will be biased toward understating the moral hazard problem. Counterfactuals will consider adjusting flood estimates to better capture future damages.

6 Supply

Developers determine the supply of development, investing with current and future rents in mind. Estimation matches changes in construction.

6.1 Model

Developers are landlords that make forward-looking investments in durable, immobile development. In each location k and period t, individual developers i begin with holdings of completed development D_{ikt} and undeveloped land L_{ikt}, with development measured in floor space. Next, they realize idiosyncratic development draws and undertake new development d_{ikt} on land ℓ_{ikt}. Development incurs construction costs but generates rental revenues once complete. Costs and revenues depend on individual actions (d_{ikt}, ℓ_{ikt}) and states (D_{ikt}, L_{ikt}), as well as aggregate state $w_{kt} = (x_{kt}, \varepsilon_{kt}, D_{kt}, \{D_{-kt}\}, L_{kt}, \{L_{-kt}\}, G_t)$, which includes observed cost factors x_{kt}, unobserved costs ε_{kt}, completed development $(D_{kt}, \{D_{-kt}\})$ across locations, undeveloped land $(L_{kt}, \{L_{-kt}\})$ across locations, and defense G_t. Time to build is one period, such that development and land follow laws of motion

$$D_{ikt+1} = D_{ikt} + d_{ikt}, \quad L_{ikt+1} = L_{ikt} - \ell_{ikt}.$$

I explicitly model the extensive-margin choice to develop or not, which lumpiness makes a key margin of variation in the data. The ex-ante value function is

$$V(D, L, w_{kt}) = r(D, w_{kt}) + \mathbb{E}[\max_{d \in \{0,1\}} \{v^d(D, L, w_{kt}) + \epsilon^d_{ikt}\}]. \tag{6}$$

Developers collect rental revenues from completed development, then consider new development subject to logit shocks ϵ^d_{ikt}. Expectations are over these shocks. Denoting dependence on state w_{kt} with kt subscripts, such that $v^1_{kt}(\cdot) \equiv v^1(\cdot, w_{kt})$, $V_{kt}(\cdot) \equiv$

$V(\cdot, w_{kt})$, and $\mathbb{E}_{kt}[\cdot] \equiv \mathbb{E}[\cdot|w_{kt}]$, the choice-specific conditional value functions are

$$v^1_{kt}(D,L) = \max_{d,\,\ell} \big\{ -c_{kt}(d,\ell) + \beta\mathbb{E}_{kt}[V_{kt+1}(D+d, L-\ell)]\big\}, \tag{7a}$$

$$v^0_{kt}(D,L) = \beta\mathbb{E}_{kt}[V_{kt+1}(D,L)], \tag{7b}$$

Developers incur construction costs if they develop, then in the next period face the same choice to develop or not. Expectations are over next-period state w_{kt+1}.

The intensive-margin choice of how much to develop trades off higher rental revenues against higher construction costs. Revenues are linear and costs are convex.

$$r_{kt}(D) = \alpha r_{kt} D, \quad c_{kt}(d,\ell) = \left(\frac{1}{2}\psi d + \phi f_{kt} + x_{kt}\gamma\right)d + \frac{1}{2}\omega\left(\frac{d}{\ell}\right)^2 + \varepsilon_{kt} \tag{8}$$

Revenues depend on completed development D and rents r_{kt}, abusing notation slightly in distinguishing r_{kt} from $r_{kt}(\cdot)$. Costs depend on new development floor space d and land use ℓ, which together determine height $h = \frac{d}{\ell}$. Convexities (ψ, ω) reflect increasing marginal costs of space and height. Observed x_{kt} capture spatial heterogeneity, including in flooding f_{kt} if flood protection involves private costs. Observed x_k also include district fixed effects that help capture unobserved heterogeneity. Unobserved ε_{kt} and idiosyncratic $\epsilon_{ikt} = \epsilon^1_{ikt} - \epsilon^0_{ikt}$ are fixed costs that influence neither floor space nor land use. Flow costs are passed onto residents and subsumed into rents. Thus, by equations 8, optimal (d,ℓ) are given by (d_{kt}, ℓ_{kt}). Where needed, superscripts differentiate demand and supply parameters as $(\alpha^d, \phi^d, \gamma^d, \varepsilon^d)$ and $(\alpha^s, \phi^s, \gamma^s, \varepsilon^s)$.

Developer supply sums over new and old development given floor space d_{kt} and probability p^{dev}_{kt} of new development in each location.

$$D^{\text{dev}}_{kt+1} = D_{kt} + d_{kt} p^{\text{dev}}_{kt}, \quad p^{\text{dev}}_{kt} = \frac{\exp\{v^1_{kt}(D,L)\}}{\exp\{v^1_{kt}(D,L)\} + \exp\{v^0_{kt}(D,L)\}} \tag{9}$$

Moving inland is costly because it abandons high-rent areas and incurs construction costs. Price endogeneity arises because rents are correlated with unobserved construction costs. Development is determined in dynamic competitive equilibrium, with rents r_{kt} that equalize demand D^{res}_{kt} and supply D^{dev}_{kt} of development in each location k and period t. Excessively high rents lead to a shortage of residential demand, while excessively low rents lead to a shortage of developer supply.

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 residential amenities, which shift local demand for development. Inverting equation 9 and substituting equations 7,

$$\ln p_{kt}^{\text{dev}} - \ln\left(1 - p_{kt}^{\text{dev}}\right) = -c_{kt}(d_{kt}, \ell_{kt}) + \beta \mathbb{E}_{kt}[V_{kt+1}(D + d_{kt}, L - \ell_{kt}) - V_{kt+1}(D, L)],$$

I avoid computing continuation values by reading them from the data in the spirit of Kalouptsidi (2014). If real estate markets are efficient, then real estate prices capture market expectations over the value of development and land holdings.

$$V_{kt}(D, L) = \alpha P_{kt}^{D} D + \alpha P_{kt}^{L} L \tag{10}$$

for property prices P_{kt}^{D} per unit of floor space and land prices P_{kt}^{L} per unit of land, where rent coefficient α monetizes utility. I substitute to eliminate continuation values, which greatly simplifies estimation.

$$\ln p_{kt}^{\text{dev}} - \ln\left(1 - p_{kt}^{\text{dev}}\right) = -c_{kt}(d_{kt}, \ell_{kt}) + \alpha\beta \mathbb{E}_{kt}[P_{kt+1}^{D} d_{kt} - P_{kt+1}^{L} \ell_{kt}]$$

Random-walk prices imply short-run expectations $\mathbb{E}_{kt}[P_{kt+1}] = P_{kt}$ and thus

$$\ln p_{kt}^{\text{dev}} - \ln\left(1 - p_{kt}^{\text{dev}}\right) = -c_{kt}(d_{kt}, \ell_{kt}) + \alpha\beta (P_{kt}^{D} d_{kt} - P_{kt}^{L} \ell_{kt}). \tag{11}$$

Identification is clearest in the simplified case with exogenous, uniform intensive-margin decisions. Here, I focus on the extensive-margin choice to develop or not.

$$d_{kt} = d_t, \quad \ell_{kt} = \ell_t, \quad h_{kt} = h_t \quad \forall\ k$$

For $P_{kt} \equiv P_{kt}^{D} - \frac{P_{kt}^{L}}{h_t}$ and $\upsilon_t \equiv \frac{1}{2}\psi d_t^2 + \frac{1}{2}\omega h_t^2$, equation 11 simplifies to

$$\ln p_{kt}^{\text{dev}} - \ln\left(1 - p_{kt}^{\text{dev}}\right) = \alpha\beta P_{kt} d_t - \phi f_{kt} d_t - d_t x_{kt} \gamma - \upsilon_t - \varepsilon_{kt}.$$

Estimation reduces to simple linear IV regression. The endogeneity problem is that unobserved costs ε_{kt} affect development supply, which influences the property and land prices (P^D_{kt}, P^L_{kt}) that determine P_{kt}.[15] The main data requirements are measures of building construction, property prices, and land prices. Indeed, such measures are available in many urban settings, although perhaps not in rural settings. Building construction data give probabilities $\hat{p}^{\text{dev}}_{kt}$ of new development, which I compute from the data in a first stage. I do so by applying a frequency estimator and smoothing nonparametrically across bins. The d_t term depends on how individual developer boundaries are defined, but it scales all regressors equally and thus affects neither estimates nor counterfactuals.[16] Prices act as numeraire, and I assume $\beta = 0.9$.

I reintroduce and endogenize intensive-margin decisions as follows. By equation 7a, floor space and land use satisfy conditions

$$[d_{kt}] \quad \frac{\partial}{\partial d} c_{kt} = \frac{\partial}{\partial d} \beta \mathbb{E}_{kt}[V_{kt+1}], \qquad [\ell_{kt}] \quad \frac{\partial}{\partial \ell} c_{kt} = \frac{\partial}{\partial \ell} \beta \mathbb{E}_{kt}[V_{kt+1}]. \tag{12}$$

It follows that equation 11 simplifies to

$$\ln p^{\text{dev}}_{kt} - \ln\big(1 - p^{\text{dev}}_{kt}\big) = \frac{1}{2}\psi d^2_{kt} - \frac{1}{2}\omega h^2_{kt} - \varepsilon_{kt} \tag{13}$$

for floor space, height, and land use as follows and $P_{kt}(h_{kt}) \equiv P^D_{kt} - \frac{P^L_{kt}}{h_{kt}}$.

$$d_{kt} = \frac{1}{\psi}\bigg(\alpha\beta P_{kt}(h_{kt}) - \phi f_{kt} - x_{kt}\gamma\bigg), \quad h_{kt} = \bigg(\frac{\alpha\beta P^L_{kt} d_{kt}}{\omega}\bigg)^{\frac{1}{3}}, \quad \ell_{kt} = \frac{d_{kt}}{h_{kt}} \tag{14}$$

Estimation applies nonlinear instrumental variables, with instruments Z and moment condition $\mathbb{E}[Z\varepsilon(\theta)]$. For parameters $\theta = (\alpha, \phi, \gamma, \psi, \omega)$, data $X_{kt} = (P^D_{kt}, P^L_{kt}, f_{kt}, x_{kt})$, and computed $\hat{p}^{\text{dev}}_{kt}$, I solve equations 14 – three equations in three unknowns – to obtain $d_{kt}(\theta)$, $h_{kt}(\theta)$, and $\ell_{kt}(\theta)$, then I solve equation 13 to obtain $\varepsilon_{kt}(\theta)$.[17] Estimation thus accommodates intensive-margin variation, but avoids exploiting it directly.[18]

[15] Consider decomposed costs $\varepsilon_{kt} = \mu_k + \tilde{\varepsilon}_{kt}$. Permanent μ_k induce strong responses from forward-looking real estate prices, even if transient $\tilde{\varepsilon}_{kt}$ do not. Estimation relies on cross-sectional data, which precludes capturing μ_k with fixed effects. Even with panel data, fixed effects do not fully capture potential persistence in $\tilde{\varepsilon}_{kt}$. Furthermore, spatial residential demand implies that location-specific shocks affect location-specific prices, even if shocks average to zero in aggregate.

[16] For $\tilde{d}_t = sd_t$ and scalar s, s affects estimates $(\hat{\alpha}, \hat{\phi}, \hat{\gamma})$ but not $(\frac{\hat{\phi}}{\hat{\alpha}}, \frac{\hat{\gamma}}{\hat{\alpha}})$. Predicted actions and welfare are also unaffected. For example, s amplifies P_{kt} but reduces $\hat{\alpha}$, such that $\frac{\hat{\alpha}}{s}\beta P_{kt} s d_t = \alpha\beta P_{kt} d_t$.

[17] Prices (P^D_{kt}, P^L_{kt}) are bundled in the simplified case, such that a single instrument is sufficient. Here, they appear separately and thus require separate instruments.

[18] I abstract entirely from the intensive-margin choice of development quality given inherent difficul-

Table 2: Developer supply estimates

	IV		First stage		
	Estimate	SE	Estimate	SE	Mean
Prices (100 USD/m^2)	0.171***	(0.041)			11.8
Residential amenities (km)			0.182***	(0.043)	2.91
Flooding (m/month)	0.064	(0.044)	-0.842***	(0.216)	0.15
Ruggedness (index)	-0.143***	(0.054)	1.268***	(0.103)	1.43
District FE	x		x		
Observations	5,780		5,780		
F-statistic			18.14		

Each observation is a 300m cell. IV estimation matches development probabilities, and the first stage is a regression with prices as the dependent variable. Prices are property prices net of land prices. Flooding is as observed from 2013 to 2020. Residential amenities is an index variable that measures proximity to schools, clinics, and passenger rail stations. By 2020 rates, 1M IDR = 70 USD. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Indeed, this variation is noisily measured and only observed on a selected sample. Appendix B shows that identification holds as in the simplified case.

6.3 Estimates

Table 2 presents supply estimates, defining locations as 300m cells. I address price endogeneity by instrumenting with residential amenities as a demand shifter, where residential amenities raise prices with a large F-statistic in the first stage. I find that supply is increasing in prices. The price coefficient captures how strongly developers respond to higher prices when sea wall construction reduces flooding and raises demand. Supply is unresponsive to flooding beyond this demand-side effect on prices, and flooding may even encourage development conditional on prices. The mean level of flooding decreases costs by a small and statistically insignificant \$5 per square meter, perhaps reflecting government intervention. Supply is decreasing in

ties in measuring it. However, I still capture quality that is correlated with floor space and land use. For example, high-rise construction may serve high-income residents that demand quality. Floor space and land use thus include quality and allow it to adjust in counterfactuals. Quality that is uncorrelated with floor space and land use is attributed to unobserved costs and held fixed in counterfactuals. If some locations demand high quality, then unobserved costs include the costs of providing it. Appendix B argues that floor space and land use account for a substantial proportion of quality, thereby mitigating this uncaptured margin.

ruggedness, consistent with its role as a supply shifter in estimating demand. The mean level of ruggedness imposes costs of $120 per square meter.

The exclusion restriction requires that residential amenities do not affect supply directly, as is reasonable if construction does not itself rely on schools and clinics. However, residential amenities may be correlated with unobserved developer amenities do affect supply. Warehouse access and building regulations are two such examples. The resulting bias will attenuate the price elasticity and understate the moral hazard problem if residential and developer amenities are negatively correlated. Indeed, warehouses locate away from schools and clinics, which bid up real estate prices by occupying land and increasing demand. And building regulations may be more loosely enforced away from residential clusters. High instrumented prices thus imply low developer amenities, muting the extent to which high prices encourage high supply.

Equation 10 is the key assumption for estimation, as it eliminates the need to compute continuation values. It states that market prices reflect expected future profits, and it holds if efficient markets push prices toward expectations. Indeed, developers eagerly develop if prices exceed expectations, leading to high supply that pushes prices down toward expectations. Similarly, developers reluctantly develop if expectations exceed prices, leading to low supply that pushes prices up toward expectations.[19] At the same time, inefficiencies like thin markets and transaction costs may persist. Estimation accommodates these inefficiencies by attributing them to unobserved costs, but counterfactuals will hold them fixed.

Estimation avoids strong restrictions on expectations. My model considers developers that make long-run decisions to develop and collect rents over time. But an isomorphic model considers developers that make short-run decisions to develop and sell outright. These developers form short-run expectations over how prices evolve between development and sale, while prices themselves embed long-run expectations. Developers then take prices as given and develop accordingly. Thus, while I specify

[19] Also consider developers with heterogeneous expectations. Pessimism avoids bias, as pessimistic developers will still develop if current prices are high. Rather than collecting rents themselves, they can develop and sell to the market. Optimism does not avoid bias, as optimistic developers may still develop if current prices are low. Rather than selling to the market, they can develop and collect rents themselves. But competitors undercut high rents, leaving optimistic developers with low rents until market prices rise to meet their optimism. And development financing is difficult if lending follows market prices. Market prices also offer coordinating information that tends to unify expectations. Each factor tempers optimism and limits bias.

short-run expectations, I can accommodate long-run expectations of any form because I observe prices. Such flexibility is crucial given the importance of government intervention in my context, as prices anticipate both flooding and intervention. At the same time, solving for counterfactuals still requires specifying long-run expectations.

Estimation also assumes atomistic developers. Large developers affect prices, such that observed prices no longer capture continuation values. Continuation values must instead be computed directly, and I lose the benefit of appealing to price data. Indeed, developers are arguably atomistic in Jakarta, where government data record 14,505 construction companies in 2021 (BPS 2022). Market segmentation may allow for market power, but the same data record 1,024 large-scale companies with annual revenues exceeding $3M (50B IDR). Competitive pressure exists even at the top end.

6.4 Alternative approaches

I compare approaches for dynamic discrete choice estimation. The full-solution approach is computationally intensive, with repeated calculation of continuation values following the nested fixed point algorithm of Rust (1987). Two-step approaches simplify computation by estimating continuation values from data, applying conditional choice probability methods from Hotz and Miller (1993).[20] Arcidiacono and Miller (2011) shows how two-step approaches can exploit finite dependence to relax assumptions on expectations and the evolution of state variables beyond the sample period, including in non-stationary models. Finite dependence holds when there exists two sequences of actions with different initial choices that eventually lead to the same distribution of states, such that continuation values difference out. The Euler conditional choice probability approach of Scott (2013) applies finite dependence to reduce estimation to linear regression, offering the benefits of finite dependence alongside straightforward estimation and transparent identification.

My approach retains the benefits of the Euler approach, but without the need to achieve finite dependence. I apply the Euler approach to Jakarta in appendix B, drawing on previous work that extends the Euler approach (Hsiao 2022). I compare

[20] Ackerberg et al. (2007), Aguirregabiria and Mira (2010), and Arcidiacono and Ellickson (2011) review this literature. Hotz and Miller (1993) and Hotz et al. (1994) develop these methods in the single-agent setting. Rust (1994) suggests expanding to multi-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.

developing today and tomorrow, and I establish finite dependence by treating development as terminal.[21] Finite dependence rules out age and cohort effects, otherwise developing tomorrow affects long-run profits. But older development may suffer from depreciation, while earlier development may avoid newer building regulations, feature older technology, or adopt different styles of design. I allow for these effects through their capitalization into prices, noting their salience in urban settings, particularly when satellite data are measured at multi-year intervals that exacerbate differences in timing. Finite dependence also requires atomistic developers, otherwise large developers influence future states and thus long-run profits. I maintain this assumption for Jakarta, where development is unconcentrated, but I can relax it in principle by estimating the effect of large development on market prices in a hedonic framework. Furthermore, the Euler approach requires long-lived developers that own land and choose the timing of development, while I accommodate short-lived entrants that buy land, develop, and sell immediately. It also requires at least two periods of data on new development, while I need only one.

7 Government

The government aims to maximize welfare. Commitment determines the extent of government intervention, as do the benefits and costs of defense. A hydrological flood model captures benefits, and engineering estimates describe costs.

7.1 Commitment

Commitment dictates the government's ability to resist static incentives in favor of dynamically optimal strategies. Under full commitment, the government announces a path of defense over time, then it adheres to this path in every subsequent period. Under no commitment, the government instead pursues sequential static optimization, choosing defense in response to development each period, while also taking prior development and defense as given. Limited commitment lies between these extremes:

[21] An alternative is to consider demolition or rebuilding as renewal actions, but both are difficult to measure in satellite data. And even if measured, each is rarer than development and thus more difficult to characterize when estimating conditional choice probabilities. Murphy (2018) also treats development as a terminal action for finite dependence, although not in an Euler framework. Scott (2013) treats crop planting as a renewal action for agricultural land use.

the government announces a path of defense for a limited period and acts accordingly, but then acts with no commitment.

Politics affect the government's objective function under limited commitment. A forward-looking government chooses defense to maximize social welfare from the current period to the terminal period. By contrast, a politically myopic government maximizes social welfare during its administration. It also considers future social benefits, which it claims credit for providing, but it ignores future social costs, which instead fall to future administrations. I abstract from political myopia for full commitment, which demands forward-lookingness, and for no commitment, which involves its own form of myopia. I also consider political lobbying with a government objective function that overweights developer profits, and I do so for each level of commitment.

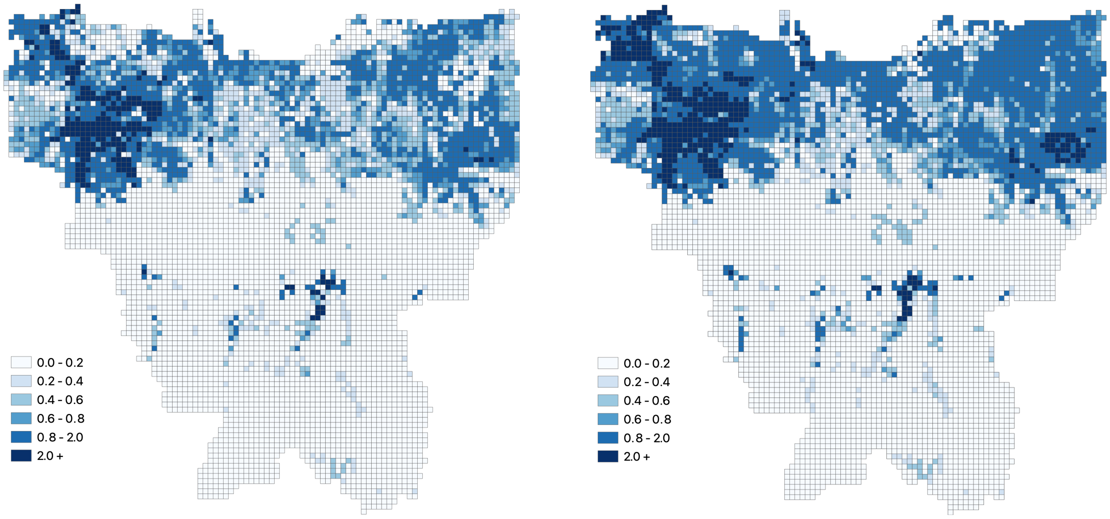
7.2 Benefits

A hydrological model of flooding captures how government defense affects flood safety across Jakarta. 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 B describes this procedure in detail.

The trained model characterizes how a sea wall affects flooding. Figure 4 shows the impact of a 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, particularly in low-elevation areas that flood regularly in the absence of defense. A small set of coastal areas benefit only modestly because flood risk is very high, such that flooding persists even with defense. At the same time, some parts of the high-elevation south also benefit from a sea wall, 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. The same model can simulate sea level rise and land

Figure 4: Reductions in flooding

(a) 3m sea wall (b) 5m sea wall



I map reductions in flood frequency, as measured in months per year, following the construction of a sea wall. I use the trained hydrological model to simulate the sea wall, raising elevation by 3m and 5m in the figures above, then I compute predicted changes in flood frequency over space.

subsidence, which each lower elevation. I also consider distributional effects given heterogeneous effects across space. I do not consider targeted sea wall construction because water can flow around partial sea walls. A sea wall must extend across Jakarta Bay in order to hold back the sea. I also ignore existing sea wall protections, which a 2020 government report calls “very poor” (NCICD 2020).

I quantify the benefits of decreased flooding with the equilibrium model of sections 5 and 6, which describe spatial demand by residents and dynamic supply by developers. Intervention decreases flooding, which raises resident demand and consumer surplus as given by the demand model. Higher demand increases rents, which raise developer supply and producer surplus as given by the supply model. Rents then adjust to balance demand and supply in equilibrium. Thus, defense encourages development, as section 4 documents for historical government intervention.

7.3 Costs

I focus on direct costs of Jakarta’s planned sea wall, omitting opportunity costs of public funds that are more difficult to quantify. I thus view these direct costs as a lower bound, noting that larger costs would amplify the moral hazard problem. I obtain engineering cost estimates from government reports on the planned wall, which runs onshore along the coast and offshore through Jakarta Bay (NCICD 2014, 2020). Onshore length is 60km with a height of 4m, while offshore length is 32km with a height of 24m, of which 8m is above water. Estimated costs are $11B in 2014 USD: construction costs of $2B onshore and $6B offshore, plus maintenance costs that add another 35% in net-present-value terms.[22] In making this investment, the government seeks protection against sea levels of up to 4m above street level, with a range of 3m to 5m expected by 2050 as land subsidence accelerates the impacts of sea level rise.

I use these estimates to project costs for sea walls of alternative heights. I assume that 1m of sea level rise requires walls with 1m of height onshore and 2m of above-water height offshore, following the ratios of the current plan. For example, relative to the planned 4m sea wall, the 3m wall of figure 4 would require 3m of height onshore and 6m offshore. I compute costs following Lenk et al. (2017), who analyze cost estimates for sea walls in Canada and the Netherlands. They find costs to be roughly linear in height and length, with little gained from computing fixed costs or higher-order terms. Indeed, I find this linearity to hold for Jakarta, where both onshore and offshore estimates imply costs of roughly $11M per meter of height and kilometer of length. For a sea wall of height g in meters, total costs $e(g)$ combine onshore and offshore unit costs of $10.67M and $10.78M per meter-kilometer, heights of g and $2g + 16$ meters, and lengths of 60 and 32 kilometers.

$$e(g) = 10.67 * 60 * g + 10.78 * 32 * (2g + 16) \quad (\$1\text{M})$$

For 3m and 5m sea walls, total costs are thus $9.5B and $12B.[23] I can also consider cost uncertainty, which Lenk et al. (2017) find is well captured by a factor of three.

[22] The 2014 plan includes 25km of offshore wall with a cost estimate of $4.8B, while the updated 2020 plan includes 32km but no cost estimate. I consider the 32km length and scale the 2014 estimate accordingly. Costs include associated flood investments in pumping stations, jetties, and mangrove restoration. I exclude non-flood investments in transport, land reclamation, and port development, which in early plans brought the total to $40B.

[23] For a 3m wall, offshore above-water and total heights are 6m and 22m. For a 5m wall, these heights are 10m and 26m. Each is relative to 8m and 24m for the planned 4m wall.

8 Counterfactuals

I quantify how coastal development and defense vary with government commitment, and I show how relocating demand affects the commitment problem.

8.1 Solving the model

First consider a one-period model with K locations. Residents choose across locations, and developers invest within locations. Under commitment, the government announces defense, and development responds accordingly. I compute development as a function of defense by solving the system of market-clearing conditions for development $d = \{d_k\}$ across locations, with K equations in K unknowns.[24]

$$d^*(g) = \{d_k \,|\, P_k^{\text{res}}(d, g) = P_k^{\text{dev}}(d_k)\}$$

I then choose defense to maximize social welfare.

$$g^* = \arg\max_g w(d^*(g), g)$$

Without commitment, defense instead responds to development. Development thus anticipates this response. I compute defense as a function of development by maximizing social welfare. I distinguish coastal development $d_{\text{co}} = \{d_{\text{co},k}\}$ from inland $d_{\text{in}} = \{d_{\text{in},k}\}$, where defense only benefits the former.

$$g^n(d_{\text{co}}) = \arg\max_g w(d_{\text{co}}, d_{\text{in}}, g)$$

I then choose development to maximize private profits.

$$d_{\text{co}}^n(d_{\text{in}}) = \arg\max_{d_{\text{co}}} \pi_{\text{co}}(d_{\text{co}}, d_{\text{in}}, g^n(d_{\text{co}}))$$
$$d_{\text{in}}^n(d_{\text{co}}) = \arg\max_{d_{\text{in}}} \pi_{\text{in}}(d_{\text{co}}, d_{\text{in}})$$

With spatial demand, profits in one location depend on development across locations.

[24] I lighten notation with P_k denoting property prices P_k^D, which capture the value of development. I suppress dependence on land prices $P_k^L(P_k^D)$, which capture the option value of development and thus reflect property prices.

Coastal profits benefit from defense, and I compute coastal development by maximizing jointly over coastal locations.[25] Inland profits do not benefit from defense, and so it is equivalent to solve the system of market-clearing conditions.

$$\hat{d}^n_{\text{in}}(d_{\text{co}}) = \{d_k \,|\, P^{\text{res}}_k(d_{\text{co}}, d_{\text{in}}, g^n(d_{\text{co}})) = P^{\text{dev}}_k(d_k)\}$$

I thus avoid maximizing jointly over inland locations. Finally, I solve for coastal and inland development as a fixed point.

$$d^n_{\text{co}}(d_{\text{in}}) = d_{\text{co}}, \quad \hat{d}^n_{\text{in}}(d_{\text{co}}) = d_{\text{in}}$$

Now consider K locations over T periods, with development $\tilde{d}_t = \{d_t, \ldots, d_T\}$ over time and $d_t = \{d_{kt}\}$ over space, as well as defense $\tilde{g}_t = \{g_t, \ldots, g_T\}$ over time. For commitment, I choose development and defense to maximize social welfare.

$$\tilde{d}^*_t, \tilde{g}^*_t = \arg\max_{\tilde{d}_t, \tilde{g}_t} \mathbb{E}_t[W_t(\tilde{d}_t, \tilde{g}_t)]$$

I do so as in the one-period case. I compute development as a function of defense by solving the system of market-clearing conditions, with KT equations in KT unknowns. That is, $\tilde{d}^*_t(\tilde{g}_t) = \{d_{kt'} \,|\, \mathbb{E}_t[P^{\text{res}}_{kt'}(\tilde{d}_t, \tilde{g}_t)] = \mathbb{E}_t[P^{\text{dev}}_{kt'}(d_{kt'})]\}$ for $k \in [1, K]$, $t' \in [t, T]$. I then compute defense by maximizing social welfare, such that $\tilde{g}^*_t = \arg\max_{\tilde{g}_t} \mathbb{E}_t[W_t(\tilde{d}^*_t(\tilde{g}_t), \tilde{g}_t)]$. Indeed, counterfactuals specify expectations.

Without commitment, I solve by backward induction. In period T, defense responds to development, and development maximizes private profits anticipating this response. Each depends on stocks of past development and defense.

$$\begin{aligned} g^n_T(d_T; DG_{T-1}) &= \arg\max_{g_T} W_T(d_T, g_T; DG_{T-1}) \\ d^n_T(DG_{T-1}) &= \arg\max_{d_T} \Pi_T(d_T, g^n_T(d_T); DG_{T-1}) \end{aligned}$$

for shorthand $DG_t = (D_t, G_t)$ and stocks $D_t = D_{t-1} + d_t$ and $G_t = G_{t-1} + g_t$. As in the one-period case, spatial demand means that development is determined jointly

[25] For example, consider coastal locations (d_1, d_2). Suppressing dependence on d_{in} and $g^n(d_{\text{co}})$, $d^n_1(d_2) = \arg\max_{d_1} \pi_1(d_1, d_2)$ and $d^n_2(d_1) = \arg\max_{d_2} \pi_2(d_1, d_2)$. It follows that (d_1, d_2) is a fixed point given by $d^n_1(d_2) = d_1$ and $d^n_2(d_1) = d_2$.

across locations. I solve disjointly then iterate to find a fixed point, again leveraging that defense only benefits coastal development.

In period $T-1$, I consider limited commitment in which the government acts with commitment in $T-1$ anticipating its non-commitment in T. Development and defense then depend on whether the government is forward-looking (^{f}) or politically myopic (^{m}). I also consider non-commitment (^{n}), which mirrors that in period T.

$$\begin{aligned} dg^f_{T-1} &= \arg\max_{dg_{T-1}} \mathbb{E}_{T-1}[W^f_{T-1}(dg_{T-1}, dg^n_T(dg_{T-1}))] \\ dg^m_{T-1} &= \arg\max_{dg_{T-1}} \mathbb{E}_{T-1}[W^m_{T-1}(dg_{T-1}, dg^n_T(dg_{T-1}))] \\ g^n_{T-1}(d_{T-1}) &= \arg\max_{g_{T-1}} \mathbb{E}_{T-1}[W_{T-1}(d_{T-1}, g_{T-1}, dg^n_T(dg_{T-1}))] \\ d^n_{T-1} &= \arg\max_{d_{T-1}} \mathbb{E}_{T-1}[\Pi_{T-1}(d_{T-1}, g^n_{T-1}(d_{T-1}), dg^n_T(d_{T-1}))] \end{aligned}$$

for shorthand $dg_t = (d_t, g_t)$ and suppressing dependence on stocks DG_{T-2}. Dynamics arise because actions in period $T-1$ affect stocks DG_{T-1} and thus actions in period T. Period $T-2$ proceeds similarly, as do earlier periods.

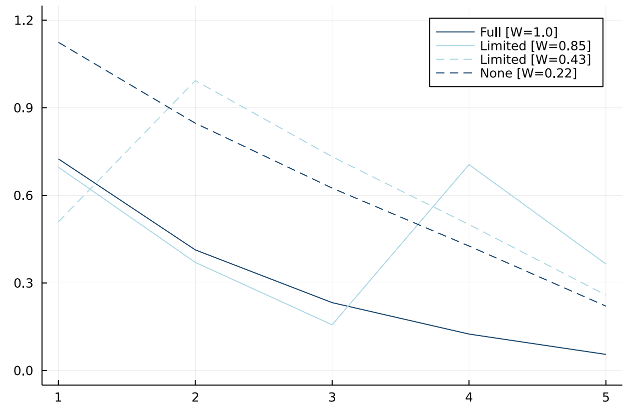
8.2 Simulations

I simulate coastal development and defense over five periods, noting that continued coastal concentration delays inland investment and thus long-run adaptation. Figure 5a considers a forward-looking government. Full commitment achieves the first best, while no commitment induces moral hazard and over-development in each period. Limited commitment involves under-development during the commitment period, lessening moral hazard in the periods that follow and reducing the resulting over-development. Figure 5b 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. The earlier government over-defends relative to full commitment, as it benefits from exploiting the later government. But it under-defends relative to no commitment, as it seeks to avoid being exploited itself. Appendix C presents the corresponding patterns of government defense.

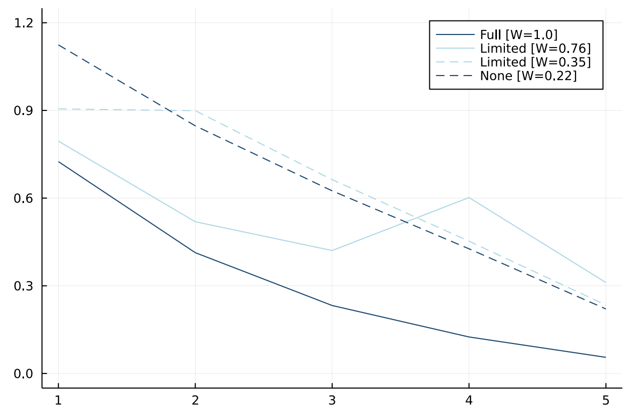
Other intervention can help navigate the fundamental commitment problem at the coast. Figure 5c considers relocating demand to reduce coastal residential value

Figure 5: New coastal development over time (d_t)

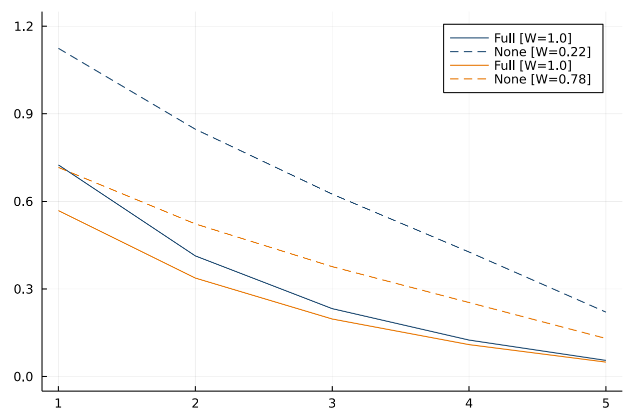
(a) Forward-looking government



(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%.

by 25%, such as with inland investments or migration subsidies. Indeed, these indirect subsidies are less likely to prompt political resistance than a direct tax. Thus, while they still require commitment, they also avoid the political difficulties that complicate commitment at the coast. Although a direct tax is more efficient, these indirect subsidies are more politically feasible. Furthermore, lowering demand reduces developers' gains from exploiting the government, lessening moral hazard and reducing over-development under non-commitment. That is, these inland policies also mitigate the coastal commitment problem. This interplay helps rationalize the moving of the political capital from Jakarta, as is currently in progress.

Table 3 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.

Table 3: Welfare effects

	L	W Baseline	W Relocating demand
Full commitment	5	1.00	1.00
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
No commitment	0	0.22	0.78

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%.

References

Abeyasekere, Susan. *Jakarta: A History*. Oxford University Press, Singapore, 1987.

Ackerberg, Daniel, C. Lanier Benkard, Steven Berry, and Ariel Pakes. Econometric Tools for Analyzing Market Outcomes. *Handbook of Econometrics*, 6A(63):4171–4276, 2007.

Aguirregabiria, Victor and Pedro Mira. Sequential Estimation of Dynamic Discrete Games. *Econometrica*, 75(1):1–53, 2007.

Aguirregabiria, Victor and Pedro Mira. Dynamic Discrete Choice Structural Models: A Survey. *Journal of Econometrics*, 156:38–67, 2010.

Almond, Douglas, Yuyu Chen, Michael Greenstone, and Hongbin Li. Winter Heating or Clean Air? Unintended Impacts of China's Huai River Policy. *American Economic Review: Papers & Proceedings*, 99(2):184–190, 2009.

Althoff, Tim, Rok Sosič, Jennifer Hicks, Abby King, Scott Delp, and Jure Leskovec. Large-Scale Physical Activity Data Reveal Worldwide Activity Inequality. *Nature*, 547:336–339, 2017.

Andreas, Heri, Hasanuddin Abidin, Irwan Gumilar, Teguh Sidiq, Dina Sarsito, and Dhota Pradipta. Insight into the Correlation between Land Subsidence and the Floods in Regions of Indonesia. *Natural Hazards - Risk Assessment and Vulnerability Reduction*, pages 39–56, 2018.

Annan, Francis and Wolfram Schlenker. Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat. *American Economic Review: Papers & Proceedings*, 105(5):262–266, 2015.

Arcidiacono, Peter and Paul Ellickson. Practical Methods for Estimation of Dynamic Discrete Choice Models. *Annual Review of Economics*, 3:363–394, 2011.

Arcidiacono, Peter and Robert Miller. Conditional Choice Probability Estimation of Dynamic Discrete Choice Models With Unobserved Heterogeneity. *Econometrica*, 79(6):1823–1867, 2011.

Badan Pusat Statistik. Statistik Konstruksi, 2022. URL https://jakarta.bps.go.id.

Bajari, Patrick, C. Lanier Benkard, and Jonathan Levin. Estimating Dynamic Models of Imperfect Competition. *Econometrica*, 75(5):1331–1370, 2007.

Bakkensen, Laura and Lint Barrage. Going Underwater? Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics. *Review of Financial Studies*, 35(8): 3666–3709, 2022.

Bakkensen, Laura and Lala Ma. Sorting Over Flood Risks and Implications for Flood Insurance Reform. *Journal of Environmental Economics and Management*, 104:102362, 2020.

Balboni, Clare. In Harm's Way? Infrastructure Investments and the Persistence of Coastal Cities. 2021.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph Shapiro. Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy*, 124(1):105–159, 2016.

Baylis, Patrick and Judson Boomhower. The Economic Incidence of Wildfire Suppression in the United States. *American Economic Journal: Applied Economics*, 2022.

Berry, Steven. Estimating Discrete-Choice Models of Product Differentiation. *RAND Journal of Economics*, 25(2):242–262, 1994.

Berry, Steven, James Levinsohn, and Ariel Pakes. Automobile Prices in Market Equilibrium. *Econometrica*, 63(4):841–890, 1995.

Boustan, Leah, Matthew Kahn, and Paul Rhode. Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century. *American Economic Review: Papers & Proceedings*, 102(3):238–244, 2012.

Budiyono, Yus, Jeroen Aerts, Brinkman JanJaap, Muh Aris Marfai, and Philip Ward. Flood Risk Assessment for Delta Mega-cities: A Case Study of Jakarta. *Natural Hazards*, 75:389–413, 2015.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro. Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock. *Econometrica*, 87(3):741–835, 2019.

Caljouw, Mark, Peter Nas, and Pratiwo. Flooding in Jakarta: Towards a Blue City with Improved Water Management. *Journal of the Humanities and Social Sciences of Southeast Asia*, 161(4):454–484, 2005.

Castro-Vincenzi, Juanma. Climate Hazards and Resilience in the Global Car Industry. 2022.

Chen, Yuyu, Avraham Ebenstein, Michael Greenstone, and Hongbin Li. Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy. *Proceedings of the National Academy of Sciences*, 110 (32):12936–12941, 2013.

Coate, Stephen. Altruism, the Samaritan's Dilemma, and Government Transfer Policy. *American Economic Review*, 85(1):46–57, 1995.

Cochrane, Joe. Jakarta, the City Where Nobody Wants to Walk. *New York Times*, 2017.

Colven, Emma. Thinking beyond Success and Failure: Dutch Water Expertise and Friction in Postcolonial Jakarta. *Environment and Planning C: Politics and Space*, 38(6):961–979, 2020.

Costinot, Arnaud, Dave Donaldson, and Cory Smith. Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World. *Journal of Political Economy*, 124(1):205–248, 2016.

Cruz, José-Luis and Esteban Rossi-Hansberg. The Economic Geography of Global Warming. 2021.

Desmet, Klaus, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg. The Geography of Development. *Journal of Political Economy*, 126(3):903–983, 2018.

Desmet, Klaus, Robert Kopp, Scott Kulp, Dávid Krisztián Nagy, Michael Oppenheimer, Esteban Rossi-Hansberg, and Benjamin Strauss. Evaluating the Economic Cost of Coastal Flooding. *American Economic Journal: Macroeconomics*, 13(2): 444–486, 2021.

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, and Maigeng Zhou. New Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy. *Proceedings of the National Academy of Sciences*, 114(39):10384–10389, 2017.

Ericson, Richard and Ariel Pakes. Markov-Perfect Industry Dynamics: A Framework for Empirical Work. *Review of Economic Studies*, 62(1):53–82, 1995.

Euromonitor International. Megacities: Developing Country Domination. 2018.

European Commission. Global Human Settlement Layer, 2022. URL https://ghsl.jrc.ec.europa.eu.

Fried, Stephie. Seawalls and Stilts: A Quantitative Macro Study of Climate Adaptation. *Review of Economic Studies*, 2022.

Garschagen, Matthias, Gusti Ayu Ketut Surtiari, and Mostapha Harb. Is Jakarta's New Flood Risk Reduction Strategy Transformational? *Sustainability*, 10(8):2934, 2018.

Glaeser, Edward and Joseph Gyourko. Urban Decline and Durable Housing. *Journal of Political Economy*, 113(2):345–375, 2005.

Gourevitch, Jesse, Carolyn Kousky, Yanjun Liao, Christoph Nolte, Adam Pollack, Jeremy Porter, and Joakim Weill. Unpriced Climate Risk and the Potential Consequences of Overvaluation in US Housing Markets. *Nature Climate Change*, 2023. doi: 10.1038/s41558-023-01594-8.

Harari, Mariaflavia and Maisy Wong. Slum Upgrading and Long-run Urban Development: Evidence from Indonesia. 2019.

Hino, Miyuki and Marshall Burke. The Effect of Information About Climate Risk on Property Values. *Proceedings of the National Academy of Sciences*, 118(17): e2003374118, 2021.

Hopenhayn, Hugo. Entry, Exit, and Firm Dynamics in Long Run Equilibrium. *Econometrica*, 60(5):1127–1150, 1992.

Hotz, V. Joseph and Robert Miller. Conditional Choice Probabilities and the Estimation of Dynamic Models. *Review of Economic Studies*, 60(3):497–529, 1993.

Hotz, V. Joseph, Robert Miller, Seth Sanders, and Jeffrey Smith. Conditional Choice Probabilities and the Estimation of Dynamic Models. *Review of Economic Studies*, 61(2):265–289, 1994.

Hsiao, Allan. Coordination and Commitment in International Climate Action: Evidence from Palm Oil. 2022.

Hsiao, Allan. Educational Investment in Spatial Equilibrium: Evidence from Indonesia. 2023.

Ibu Kota Negara, 2022. URL https://ikn.go.id.

Intergovernmental Panel on Climate Change. Special Report on the Ocean and Cryosphere in a Changing Climate. 2019.

Jati, Muhammad, Suroso, and Purwanto Santoso. Prediction of Flood Areas Using the Logistic Regression Method (Case Study of the Provinces Banten, DKI Jakarta, and West Java). *Journal of Physics: Conference Series*, 1367:012087, 2019.

Jia, Ruixue, Xiao Ma, and Victoria Wenxin Xie. Expecting Floods: Firm Entry, Employment, and Aggregate Implications. 2022.

Jofre-Benet, Mireia and Martin Pesendorfer. Estimation of a Dynamic Auction Game. *Econometrica*, 71(5):1443–1489, 2003.

Kalouptsidi, Myrto. Time to Build and Fluctuations in Bulk Shipping. *American Economic Review*, 104(2):564–608, 2014.

Kleinman, Benny, Ernest Liu, and Stephen Redding. Dynamic Spatial General Equilibrium. *Econometrica*, 91(2):385–424, 2023.

Kocornik-Mina, Adriana, Thomas McDermott, Guy Michaels, and Ferdinand Rauch. Flooded Cities. *American Economic Journal: Applied Economics*, 12(2):35–66, 2020.

Kopp, Robert, Radley Horton, Christopher Little, Jerry Mitrovica, Michael Oppenheimer, D. J. Rasmussen, Benjamin Strauss, and Claudia Tebaldi. Probabilistic 21st and 22nd Century Sea-Level Projections at a Global Network of Tide-Gauge Sites. *Earth's Future*, 2(8):383–406, 2014.

Kousky, Carolyn, Erzo Luttmer, and Richard Zeckhauser. Private Investment and Government Protection. *Journal of Risk and Uncertainty*, 33(1/2):73–100, 2006.

Kousky, Carolyn, Erwann Michel-Kerjan, and Paul Raschky. Does Federal Disaster Assistance Crowd Out Flood Insurance? *Journal of Environmental Economics and Management*, 87:150–164, 2018.

Kulp, Scott and Benjamin Strauss. New Elevation Data Triple Estimates of Global Vulnerability to Sea-Level Rise and Coastal Flooding. *Nature Communications*, 10: 4844, 2019.

Kydland, Finn and Edward Prescott. Rules Rather than Discretion: The Inconsistency of Optimal Plans. *Journal of Political Economy*, 85(3):473–492, 1977.

Lenk, Stephan, Diego Rybski, Oliver Heidrich, Richard Dawson, and Jürgen Kropp. Costs of Sea Dikes – Regressions and Uncertainty Estimates. *Natural Hazards and Earth System Sciences*, 17:765–779, 2017.

Lin, Yatang, Thomas McDermott, and Guy Michaels. Cities and the Sea Level. 2022.

Luo, Pingping, Shuxin Kang, Apip, Meimei Zhou, Jiqiang Lyu, Siti Aisyah, Mishra Binaya, Ram Krishna Regmi, and Daniel Nover. Water Quality Trend Assessment in Jakarta: A Rapidly Growing Asian Megacity. *PLoS ONE*, 14(7):e0219009, 2019.

Mosavi, Amir, Pinar Ozturk, and Kwok-wing Chau. Flood Prediction Using Machine Learning Models: Literature Review. *Water*, 10(11):1536, 2018.

Mulder, Philip. Mismeasuring Risk: The Welfare Effects of Flood Risk Information. 2022.

Murphy, Alvin. A Dynamic Model of Housing Supply. *American Economic Journal: Economic Policy*, 10(4):243–267, 2018.

Nath, Ishan. Climate Change, the Food Problem, and the Challenge of Adaptation through Sectoral Reallocation. 2022.

National Capital Integrated Coastal Development Project. Master Plan. 2014.

National Capital Integrated Coastal Development Project. Kajian Lingkungan Hidup Strategis: Rencana Perlindungan Banjir Terpadu atau Integrated Flood Safety Plan (IFSP). 2020.

Nicholls, Robert, Daniel Lincke, Jochen Hinkel, Sally Brown, Athanasios Vafeidis, Benoit Meyssignac, Susan Hanson, Jan-Ludolf Merkens, and Jiayi Fang. A Global Analysis of Subsidence, Relative Sea-Level Change and Coastal Flood Exposure. *Nature Climate Change*, 11:338–342, 2021.

Octavianti, Thanti and Katrina Charles. The Evolution of Jakarta's Flood Policy over the Past 400 Years: The Lock-in of Infrastructural Solutions. *Environment and Planning C: Politics and Space*, 37(6):1102–1125, 2019.

Ostriker, Abby and Anna Russo. The Effects of Floodplain Regulation on Housing Markets. 2022.

Pakes, Ariel, Michael Ostrovsky, and Steven Berry. Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples). *RAND Journal of Economics*, 38(2):373–399, 2007.

Peltzman, Sam. The Effects of Automobile Safety Regulation. *Journal of Political Economy*, 83(4):677–726, 1975.

Pemerintah Provinsi DKI Jakarta, 2022. URL https://jakartasatu.jakarta.go.id.

Pesendorfer, Martin and Philipp Schmidt-Dengler. Asymptotic Least Squares Estimators for Dynamic Games. *Review of Economic Studies*, 75(3):901–928, 2008.

Riley, Shawn, Stephen DeGloria, and Robert Elliot. A Terrain Ruggedness Index that Quantifies Topographic Heterogeneity. *Intermountain Journal of Sciences*, 5 (1-4):23–27, 1999.

Rust, John. Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher. *Econometrica*, 55(5):999–1033, 1987.

Rust, John. Structural Estimation of Markov Decision Processes. *Handbook of Econometrics*, 4(51):3081–3143, 1994.

Scott, Paul. Dynamic Discrete Choice Estimation of Agricultural Land Use. 2013.

Taftazani, Riza, Shinobu Kazama, and Satoshi Takizawa. Spatial Analysis of Groundwater Abstraction and Land Subsidence for Planning the Piped Water Supply in Jakarta, Indonesia. *Water*, 14(20):3197, 2022.

Takagi, Hiroshi, Miguel Esteban, Takahito Mikami, and Daisuke Fujii. Projection of Coastal Floods in 2050 Jakarta. *Urban Climate*, 17:135–145, 2016.

United States Army Corps of Engineers. New York-New Jersey Harbor and Tributaries Coastal Storm Risk Management Feasibility Study. 2022.

van de Wal, R. S. W., R. J. Nicholls, D. Behar, K. McInnes, D. Stammer, J. A. Lowe, J. A. Church, R. DeConto, X. Fettweis, H. Goelzer, M. Haasnoot, I. D. Haigh, J. Hinkel, B. P. Horton, T. S. James, A. Jenkins, G. LeCozannet, A. Levermann, W. H. Lipscomb, B. Marzeion, F. Pattyn, A. J. Payne, W. T. Pfeffer, S. F. Price, H. Seroussi, S. Sun, W. Veatch, and K. White. A High-End Estimate of Sea Level Rise for Practitioners. *Earth's Future*, 10(11):e2022EF002751, 2022.

Vigdor, Jacob. The Economic Aftermath of Hurricane Katrina. *Journal of Economic Perspectives*, 22(4):135–154, 2008.

Wagner, Katherine. Adaptation and Adverse Selection in Markets for Natural Disaster Insurance. *American Economic Journal: Economic Policy*, 14(3):380–421, 2022.

Ward, Philip, Muh Aris Marfai, Poerbandono, and Edvin Aldrian. Climate Adaptation in the City of Jakarta. *Climate Adaptation and Flood Risk in Coastal Cities*, pages 285–304, 2011.

Wijayanti, Pini, Xueqin Zhu, Petra Hellegers, Yus Budiyono, and Ekko van Ierland. Estimation of River Flood Damages in Jakarta, Indonesia. *Natural Hazards*, 86: 1059–1079, 2017.

APPENDIX

A Data

Table A1 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 Visicom measures is 0.90 for built-up surface and 0.92 for built-up volume. Figure A1 shows the comparison visually.

Property prices

I construct property prices 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.

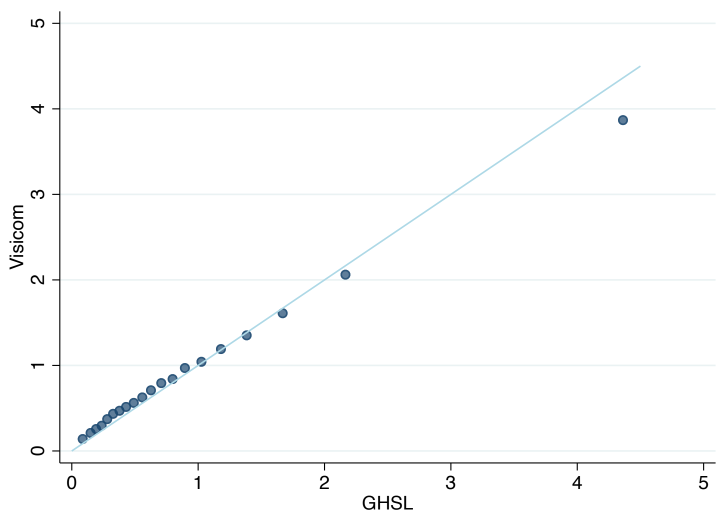
Second, I geolocate listings with the Google Maps API. As inputs, I supply property addresses, types, and districts. Property addresses include street names and sometimes street numbers. I identify street names with the keyword *jalan* where possible. For apartments, I also include apartment complex 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 1km avoids dropping data excessively while maintaining accuracy at the tract level. Table A2 shows the high rate of success in geocoding.

Third, I construct property prices at the 300m cell level. I compute prices per square 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

Table A1: Data sources

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

Figure A1: 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.

Table A2: 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.

Table A3: 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).

– 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.[26] I thus obtain property prices for 2022.

Fourth, I backcast the 2022 prices 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 prices 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 prices. Relying directly on the 2015 prices 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 A3 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

[26] For the inverse distance weighting, I use a weighting power of two, a smoothing parameter of zero, a search circle radius of 1km, a maximum of 20 observations, and a minimum of five observations. I include observations from the periphery of Jakarta.

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 A2. I select these points to prioritize accuracy in the vicinity of the National Monument and 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 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 A3 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 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 A4 draws on data from the full panel to measure the discontinuity in each available year. For cell c and year t, the specification is

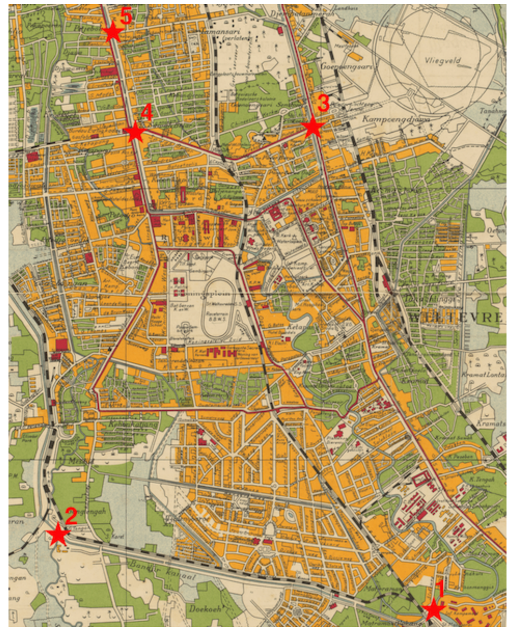
$$Y_{ct} = \alpha + \sum_{t'} \beta_{t'} N_c \mathbb{1}[t' = t] + \delta_c + \delta_t + \varepsilon_{ct}$$

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 to this choice. The coefficients of interest are the β terms by year. Cell and year

Figure A2: Ground control points for georeferencing

(a) Pre-1918 maps

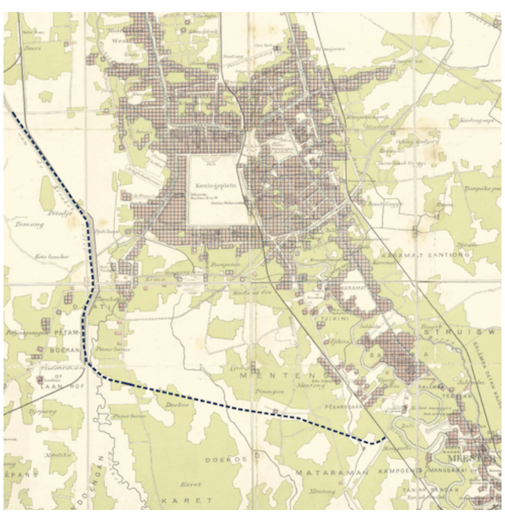
(b) Post-1918 maps



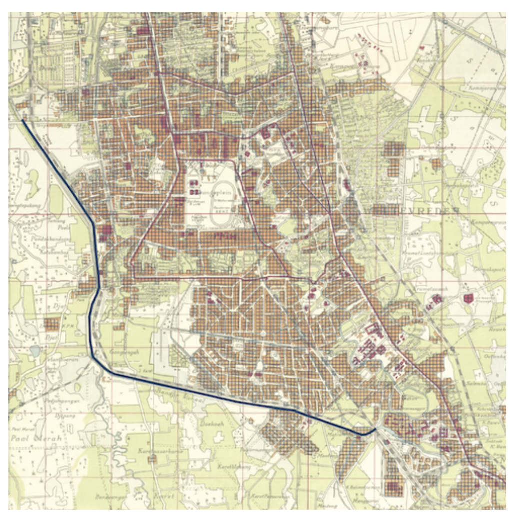
Red stars mark the five ground control points used for georeferencing.

Figure A3: Land development and the West Flood Canal

(a) Before (1904)



(b) After (1945)



Red shading denotes developed lands, and square boxes mark 50m 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.

Table A4: 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

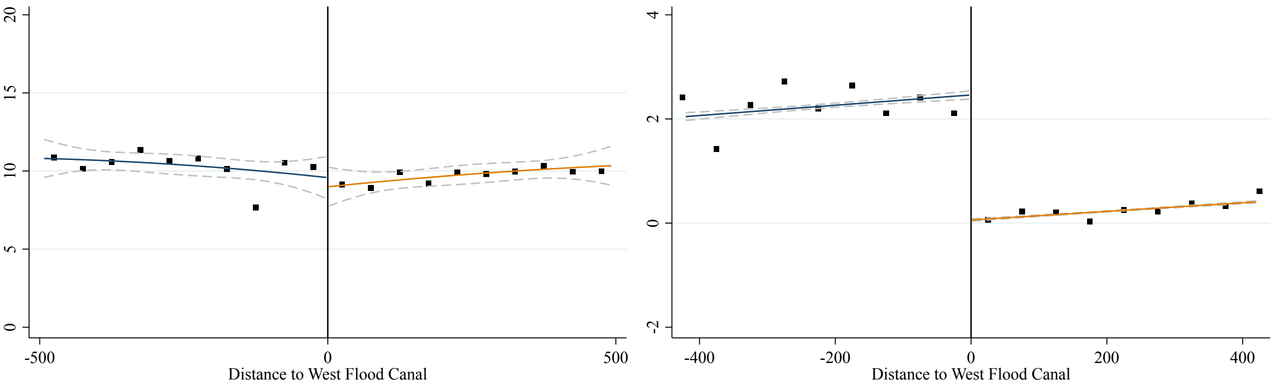
Data on historical land development come from Dutch colonial maps. The West Flood Canal was completed in 1918 and protected neighborhoods to its north, but not to its south. The dependent variable is land development, and each observation is a 100m cell. The optimal bandwidth is 500m. Robust standard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

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 A4 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 prices and more building construction in 2015. Table A5 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.

Figure A4: Validating the spatial regression discontinuity design

(a) Elevation (b) Flood frequency (2013-2020)



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 cell. The x-axis measures distance to the West Flood Canal in meters, and 500m is the optimal bandwidth.

Table A5: Flood risk, land prices, and building construction

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

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 price ($\$/\text{m}^2$)	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 prices are from the Jakarta Smart City initiative for 2015, and building construction is from the Global Human Settlement Layer for 2015. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Estimation

Identification with endogenous intensive-margin decisions

Prices again act as numeraire. Applying equations 14, I express equation 13 in terms of intensive-margin choice $h_{kt}(X_{kt};\theta)$ for data X_{kt} and parameters θ.

$$\ln p_{kt}^{\text{dev}} - \ln\bigl(1-p_{kt}^{\text{dev}}\bigr) = \tilde{\psi}\left(\alpha P_{kt}^{D} - \frac{\alpha P_{kt}^{L}}{h_{kt}} - \phi f_{kt}\right)^{2} - \tilde{\omega} h_{kt}^{2} - \varepsilon_{kt}$$

for $\tilde{\psi} \equiv \frac{1}{2\psi}$, $\tilde{\omega} \equiv \frac{\omega}{2}$. I drop $(x_{kt}\gamma, \beta)$ for simplicity. Expanding (X_{kt}, θ) terms,

$$\Gamma_1(X_{kt};\theta) = \tilde{\psi}\alpha^2\bigl(P_{kt}^{D}\bigr)^2 - \tilde{\psi}\alpha\phi\bigl(2P_{kt}^{D} f_{kt}\bigr) + \tilde{\psi}\phi^2\bigl(f_{kt}^2\bigr),$$

For coefficients $(\beta_1, \beta_2, \beta_3) = (\tilde{\psi}\alpha^2, \tilde{\psi}\alpha\phi, \tilde{\psi}\phi^2)$, $\frac{\beta_2}{\beta_1}$, $\frac{\beta_3}{\beta_2}$, and $\frac{\beta_3}{\beta_1}$ each identify relative parameter $\frac{\phi}{\alpha}$, but (ψ, α, ϕ) are not separately identified. Expanding h_{kt} terms,

$$\Gamma_2(h_{kt}, X_{kt};\theta) = -\tilde{\psi}\alpha^2\left(\frac{2P_{kt}^{D}P_{kt}^{L}}{h_{kt}}\right) + \tilde{\psi}\alpha\phi\left(\frac{2P_{kt}^{L} f_{kt}}{h_{kt}}\right) + \tilde{\psi}\alpha^2\left(\frac{P_{kt}^{L}}{h_{kt}}\right)^2 - \tilde{\omega} h_{kt}^2.$$

For exogenous h_{kt}, coefficients $(\beta_4, \beta_5, \beta_6) = (\tilde{\psi}\alpha^2, \tilde{\psi}\alpha\phi, \tilde{\psi}\alpha^2)$ identify no more than identified previously. But for endogenous h_{kt}, convexity ψ has level effects: by equations 14, larger convexity implies smaller (d_{kt}, h_{kt}). Fixing $(\tilde{\psi}\alpha^2, \tilde{\psi}\alpha\phi, \tilde{\psi}\phi^2)$, as identified previously, varying ψ affects h_{kt} and in turn affects ε_{kt} and the moment condition. I thus separately identify (ψ, α, ϕ), with a similar argument for ω. Intuitively, convexity affects intensive-margin choices in levels (monotonically), and these choices affect development profits and probabilities. Inverting development probabilities thus yields convexity in levels. Overidentification motivates estimation by GMM.

Variation in development quality

On the intensive margin, the model focuses on choice over development floor space and land use. I abstract from quality because of difficulties in observing it. Table B1 analyzes price dispersion in an attempt to assess quality. I find that floor space and land use can explain nearly half of variation in property prices per square meter, both across properties and across locations. Quality is thus partially captured by floor space and land use, such that cost estimates along these margins will reflect the costs of providing quality. I observe only two potential measures of quality at the property level: number of bedrooms and number of bathrooms. I find that these measures provide little more explanatory power beyond floor space and land use, suggesting that quality remains largely unobserved.

At the same time, I would not expect floor space and land use to account fully

Table B1: Explaining price dispersion (R^2)

Regressors	Properties	Locations
Floor space, land use	0.4436	0.4178
+ Bedrooms, bathrooms	0.4483	0.4405
+ Residential amenities	0.5369	0.5372

Each cell is the R^2 of one nonparametric kernel regression, with property prices per square meter as the dependent variable. The second and third rows add new regressors while keeping previous regressors. The first column considers variation across properties, and the second column considers variation across locations, which I define as 300m cells. I include district fixed effects, and I omit the top and bottom 1% of property prices.

for price variation, even if development quality were perfectly correlated with these decisions. The reason is that not all price variation comes from development quality. Amenities affect prices from the demand side, and including observed amenities explains another 10% of the price variation. Including unobserved amenities would explain more. Similarly, construction costs affect prices from the supply side. Thus, the above provides an upper bound on the extent of this uncaptured quality.

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. Each involves land use ℓ_{kt}. Intuitively, developing tomorrow reduces upfront costs given discounting, but it also delays the arrival of rental revenue. Choice-specific conditional value functions are

$$\begin{aligned}
v^1_{kt}(D,L) &= -c_{kt}(d_{kt},\ell_{kt}) + \beta\mathbb{E}_{kt}[\alpha r_{kt+1}D + \alpha r_{kt+1}d_{kt} - \ln\bigl(1-p^{\text{dev}}_{kt+1}\bigr)] && \text{(15a)}\\
&\quad + \beta^2\mathbb{E}_{kt}[V_{kt+2}(D+d_{kt}, L-\ell_{kt})],\\
v^0_{kt}(D,L) &= \beta\mathbb{E}_{kt}[\alpha r_{kt+1}D - c_{kt+1}(d_{kt},\ell_{kt}) - \ln p^{\text{dev}}_{kt+1}] && \text{(15b)}\\
&\quad + \beta^2\mathbb{E}_{kt}[V_{kt+2}(D+d_{kt}, L-\ell_{kt})]\\
&\quad + \frac{1}{2}\beta\mathbb{E}_{kt}[c''_{kt}(d_{kt})(d_{kt+1}-d_{kt})^2 + c''_{kt}(h_{kt}(\ell_{kt}))(h_{kt+1}(\ell_{kt+1}) - h_{kt}(\ell_{kt}))^2].
\end{aligned}$$

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.

$$\begin{aligned}
V_{kt}(D,L) - \alpha r_{kt}D = v^1_{kt}(D,L) - \ln p^{\text{dev}}_{kt} &= v^0_{kt}(D,L) - \ln\bigl(1-p^{\text{dev}}_{kt}\bigr),\\
v^1_{kt}(D,L,d,\ell) &= v^1_{kt}(D,L) - \frac{1}{2}c''_{kt}(d_{kt})(d_{kt}-d)^2 - \frac{1}{2}c''_{kt}(h_{kt})(h_{kt}(\ell_{kt}) - h(\ell))^2
\end{aligned}$$

Table B2: Comparing models

	R^2	MAE	RMSE
Multiple linear regression	0.027	2.467	3.778
Decision tree	0.225	2.035	3.336
Bagging	0.433	1.676	2.959
Random forest	0.458	1.596	2.797
Gradient boosting decision tree	0.467	1.608	2.800
Histogram GBDT	0.466	1.617	2.796
Histogram GBDT with monotonicity	0.471	1.606	2.827

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.

for $v^1_{kt}(D, L) = \max_{d,\ell}\{v^1_{kt}(D, L, d, \ell)\}$. The first line is a special case of Arcidiacono and Miller (2011) Lemma 1, and the second is as derived in Hsiao (2022). Inverting equation 9 and substituting equations 15, continuation values V_{kt+2} cancel under finite dependence. For $\Delta X_{kt} = X_{kt} - \beta X_{kt+1}$ and $\tilde{X}_{kt} = X_{kt} - X_{kt+1}$,

$$\Delta \ln p^{\text{dev}}_{kt} - \Delta \ln\big(1 - p^{\text{dev}}_{kt}\big) = -\Delta c_{kt}(d_{kt}, \ell_{kt}) + \alpha\beta r_{kt+1} d_{kt} - \frac{1}{2}\beta\psi \tilde{d}^2_{kt} - \frac{1}{2}\beta\omega\tilde{h}^2_{kt} + \eta_{kt}$$

given expectational errors η_{kt}, which by rational expectations are mean zero (correct on average) and orthogonal (use all in information set $\mathcal{J}_{kt}$). I thus proxy for unobserved expectations with observed realizations.

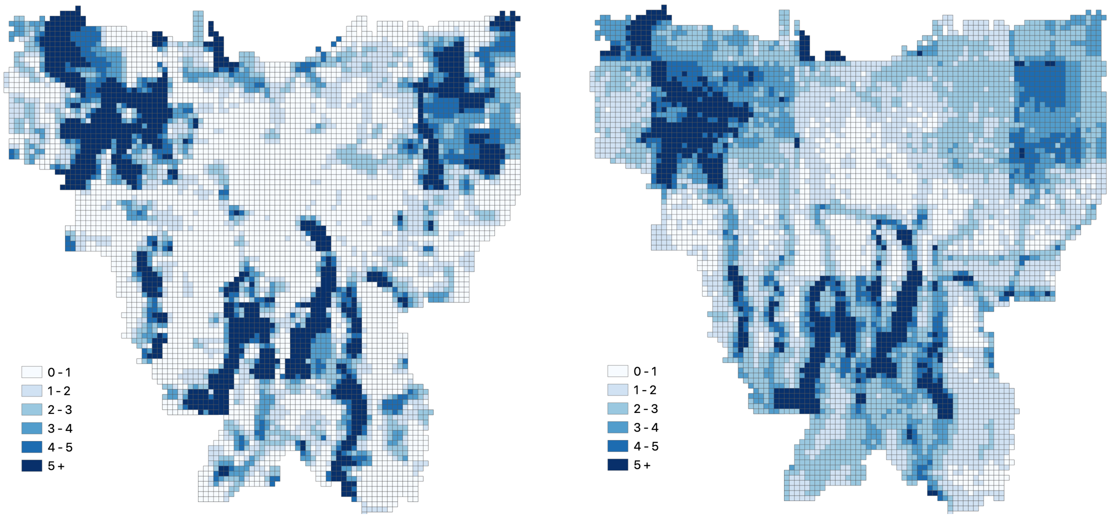
Hydrological model of flooding

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 2013 to 2020. I compute average annual rainfall. Elevation data at a resolution of 90m come from the Shuttle Radar Topography Mission (SRTM) digital elevation model. I calculate slopes from elevation data

Figure B1: Hydrological model fit

(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.

by computing slope as the angle of terrain inclination. I compute river and coastal distances with OpenStreetMap 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 B2 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-learn* package in Python, which yields model parameters of 12 for maximum tree depth, 300 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 B1 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

Table B3: Feature importance

Feature	Importance
Annual rainfall	0.590
Distance to major rivers	0.586
Distance to the coast	0.487
Elevation	0.418
Distance to minor rivers	0.372
Slope	0.174

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.

upstream watersheds capture fluvial and pluvial flooding historically, while distance to the coast and elevation capture growing coastal flooding. Table B3 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 rainfall, distance to major rivers, and distance to the coast being of primary importance, and distance to minor rivers and slope being less pivotal.

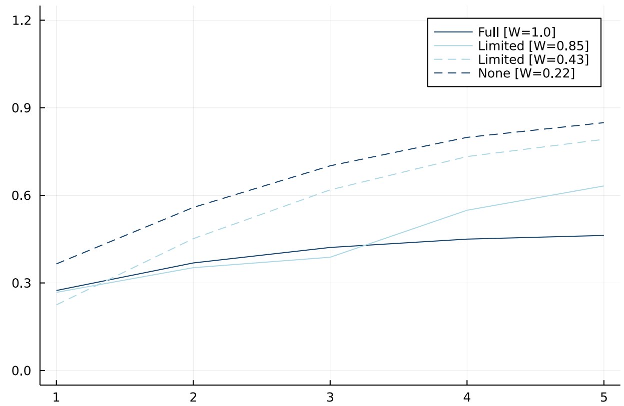
I simulate sea wall construction, sea level rise, and land subsidence by manipulating elevation and computing predicted changes in flooding. I thus benefit from large, observed variation in elevation across Jakarta, while avoiding the need for more complex models of flooding. For sea wall construction, I raise the elevation of Jakarta uniformly by the height of the sea wall. A sea wall thus benefits areas both above and below sea level, as well as both within and beyond the flood zone. Indeed, a sea wall reduces inundation for areas below sea level, as well as storm-surge risk for areas above sea level. Similarly, a sea wall prevents ruin and its spillovers, offering direct benefits within the flood zone, as well as indirect benefits beyond the flood zone. Since elevation is relative to sea level, I simply treat sea level rise as lowering elevation uniformly and land subsidence as lowering elevation heterogeneously.

C Counterfactuals

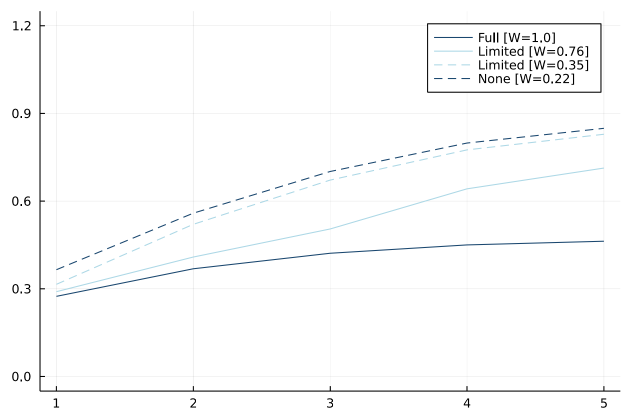
Figure C1 plots simulated government defense over time. Non-commitment leads to higher defense than under full commitment. Limited commitment prompts initial under-defense relative to the first best, which mitigates future moral hazard, but only when the current government is forward-looking. Otherwise 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: Coastal defense over time (g_t)

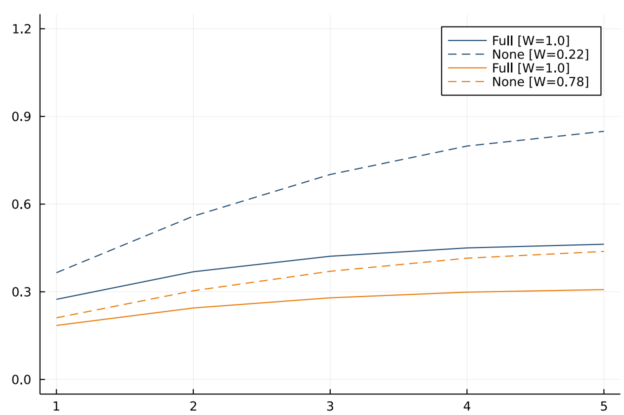
(a) Forward-looking government



(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%.