Sea Level Rise and Urban Adaptation in Jakarta

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

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1 Introduction

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

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

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

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

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

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

I study how this response creates a commitment problem for future government intervention. I do so quantitatively with a dynamic spatial model of urban development and a focus on Jakarta's planned sea wall. In the model, developers and residents make investment and location decisions with 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. Total supply arises as a dynamic competitive equilibrium among atomistic developers, as in Hopenhayn (1992), and rents clear markets for development, equalizing residential demand and developer supply in each period. The government intervenes with a sea wall, as informed by a hydrological model of how sea wall construction affects flooding across locations.

Estimation leverages granular data on developers, residents, and flooding. I estimate residential demand by matching changes in the spatial distribution of population between 2015 and 2020. Estimation mirrors Berry et al. (1995), integrating over origins and addressing the endogeneity of rents with instruments. I estimate developer supply by matching the spatial distribution of new construction between 2015 and 2020. Estimation 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 offer a direct measure of expectations, which I can accommodate flexibly, including over government intervention. Finally, I follow the frontier of the hydrological literature in training a machine-learning model of flooding with monthly,

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

tract-level data on flooding from 2013 to 2020. A histogram gradient boosting decision tree fits the data well and provides sensible predictions for how sea wall construction decreases flooding over space.

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

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

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

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

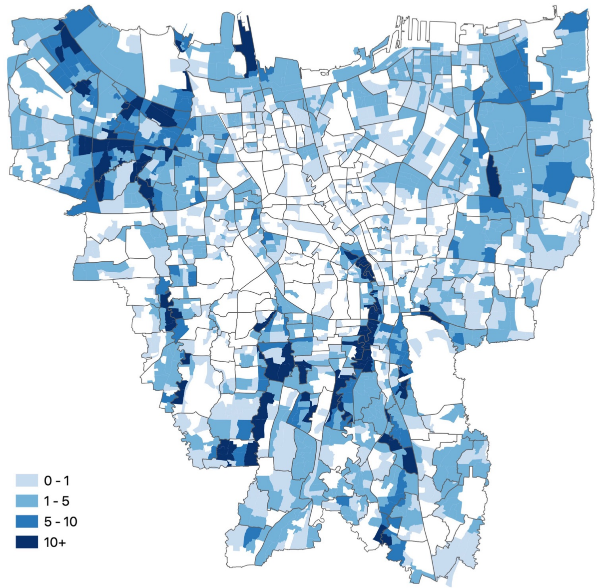
2 Background

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

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

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

Figure 1: Flood frequency (2013-2020)



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

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

Coastal flooding adds significant additional risk in the coming decades. North Jakarta faces near total submersion by 2050, as sea level rise combines with rapid land subsidence. Projected subsidence in some coastal neighborhoods exceeds 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). Indeed, water demand continues to rise with Jakarta's growing population, but surface water reserves remain fixed and undermined by high pollution levels, poor treatment systems, and limited piping infrastructure (Luo et al. 2019). Efforts to quell subsidence thus face fundamental difficulties.

Figure 2: Flood infrastructure

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

These existential threats to the nation's capital have prompted two major government initiatives. First, a sea wall has been in discussion since 2011, with costs as high as $40 billion (Garschagen et al. 2018, Colven 2020). Proposals have varied in scope and ambition, but each has prioritized onshore walls for short-term protection. The Jakarta Coastal Defense Strategy (JCDS) in 2011 became the National Capital Integrated Coastal Development Masterplan (NCICD) in 2014 – the so-called "Great Garuda Project" – and was further revised in 2016. Progress then slowed with a 2016 moratorium and the 2017 election of Anies Baswedan, whose gubernatorial campaign called for halting construction. Work resumed in 2019 with the Integrated Flood Safety Plan (IFSP).

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

3 Theory

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

3.1 Development and defense

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

The government chooses defense to maximize social welfare, while developers choose development with private profits in mind. Welfare and profits are

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

for net present values (W_t, Π_t) and current terms (w_t, π_t). Developers do not internalize costs $e(g_t)$ of defense, and so the first best requires correcting this uninternalized

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

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

7 For expositional simplicity, this section considers nondurable defense that requires repeated intervention. Such a model is isomorphic to one with durable defense but repeated intervention due to rising sea levels. The empirical model does include durable defense.

externality.[8] However, the government faces a commitment problem in doing so: it tends to defend development ex post despite not wanting to ex ante, and developers take advantage to force defense at suboptimally high levels.

3.2 Commitment

Over-development arises when the government lacks commitment power. Consider the one-period case with a single round of interaction between the government and developers. Setting $D_0 = 0$ for simplicity, social welfare and private profits are

$$W = r(d, g) - c(d) - e(g),$$
$$\Pi = r(d, g) - c(d).$$

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

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

for $r'(x) = \frac{\partial}{\partial x} r(d, g)$. Both lines equalize marginal benefits and costs.[9]

Without commitment, the government revises its choice of defense after development is sunk, and developers act anticipating this response. Developers enter until profits are driven to zero, where profits for the marginal developer are

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

for defense that responds to development. The zero-profit condition for the marginal developer and the first order condition for government defense are

$$[d^n] \quad r'(d) + r'(g)\, g'(d) = c'(d), \tag{2a}$$
$$[g^n] \quad r'(g) = e'(g). \tag{2b}$$

[8] Developers do internalize their own investment in flood-defensive development, as captured by $c(d)$. But government-funded defense crowds out this private investment.

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

The result is over-development $d^n > d^*$ relative to the first best, which I prove by comparing conditions 1 and 2. First, defense increases with sunk development. Differentiating equation 2b with respect to development,

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

It follows that $g'(d) > 0$ given $\kappa > 0$, $r''(g) < 0$, and $e''(g) \geq 0$. Second, this response creates moral hazard, as over-development anticipates over-defense.[10] In equation 2a, $g'(d) > 0$ implies $d^n > d^*$ given $r'(g) > 0$, $r''(d) < 0$, and $c''(d) \geq 0$. Moral hazard raises developer returns and thus development.

Commitment avoids over-development but faces political economy challenges. Committing to first-best defense g^* eliminates moral hazard, as it implies $g'(d) = 0$. However, the government finds it optimal to protect over-development ex post, particularly if lobbying or upcoming elections increase its returns to doing so. Targeting first-best development d^* also eliminates moral hazard. Tax $e(g)$ on development forces developers to internalize the costs of defense, implying profit condition

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

which coincides with equation 1a given equation 2b. Restricting permits or zoning achieves similar outcomes by regulating quantities instead of prices. However, taxes and restrictions still require commitment of enforcement. Indeed, developers will lobby against these policies, particularly if lobbying is facilitated by corruption.

That is, the government tends to bail out developers. The commitment problem is mitigated if developers faces the costs of defense in other forms. For example, a budget-constrained local government might reduce other services or increase future taxes. But funding can also come from external sources. Internationally, the World Bank administers the Adaptation Fund, which supports climate-adaptation projects worldwide, and the International Monetary Fund has proposed the Resilience and Sustainability Trust with similar aims. Domestically, national and regional governments fund local adaptation. In Jakarta, national government agencies manage the

[10] Note that atomistic marginal developer d does not itself affect residential values or defense, but that its revenues $r'(d) + r'(g)\, g'(d)$ are set by mass $[0, d)$ of inframarginal developers. The typical zero-profit condition features the same intuition for prices, with entrants that act as price-takers individually but face downward-sloping demand collectively.

sea wall project. Elsewhere, sea wall plans for New York City propose 65% federal funding and 35% state funding (USACE 2022). Even locally, inland residents help fund coastal defense despite not benefiting directly. The commitment problem holds as long as coastal defense is not funded solely by coastal developers.

The commitment problem is also mitigated by the stock of existing development ($D_0 > 0$). If defense largely responds to existing rather than new development, then new developers have limited ability to force over-defense. But existing development depreciates, particularly over the long run, thereby restoring the impact of new development. Similarly, political bias may give added weight to new development, as politicians claim credit and developers lobby for new construction. In either case, existing development was itself once new, and today's static incentive to defend it remains consistent with yesterday's commitment problem.

Finally, the commitment problem is trivially solved if the government lacks the capacity to defend. If an ineffective government is constrained to $g = 0$, then $g'(d) = 0$ eliminates moral hazard (but defense $g < g^*$ will be suboptimally low). However, governments with capacity to defend face considerable pressure to do so. In Indonesia, government plans state that "abandoning" Jakarta is "not considered ... a viable option," citing the city's sizable population and economic value (NCICD 2014). Furthermore, public works projects are both politically popular and opportunities for corruption (Olken 2007). Beyond Indonesia, flood damages are salient to voters, and inaction has political consequences.

3.3 Commitment over time

The commitment problem features rich dynamics. Consider the two-period case with multiple interactions between the government and developers. In the first best, the government chooses development and defense across periods to maximize social welfare $W_1 = w_1 + \beta w_2$. The resulting first order conditions are

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

for $r_t'(x) = \frac{\partial}{\partial x} r(D_t, g_t)$. Each line equalizes marginal benefits and costs.[11]

Without commitment in period two, the government chooses g_2 to maximize welfare W_2, and developers choose d_2 considering profits π_2. The resulting equilibrium conditions mirror equations 2.

$$[d_2^n] \quad r_2'(d_2) + r_2'(g_2)g_2'(d_2) = c'(d_2), \tag{3a}$$

$$[g_2^n] \quad r_2'(g_2) = e'(g_2) \tag{3b}$$

Period one depends on government commitment. Under limited commitment, the government chooses (d_1, g_1) in period one. Under no commitment, the government chooses g_1 while developers set d_1 with π_1 in mind. Each case anticipates no commitment in period two. Government horizon introduces another dimension of political economy. A forward-looking government $(^f)$ maximizes W_1, while a politically myopic government $(^m)$ instead maximizes $w_1 + \beta r_2$ for $r_t = r(D_t, g_t)$. The latter government weighs future benefits, for which it claims political credit, but it ignores future costs, which are incurred under subsequent administrations. For development, the equilibrium conditions depend on commitment and horizon.

$$[d_1^f] \quad r_1'(d_1) + \beta r_2'(d_1) = c'(d_1) + \beta r_2'(g_2)g_2'(d_1), \tag{4a}$$

$$[d_1^m] \quad r_1'(d_1) + \beta r_2'(d_1) + \beta r_2'(d_2)d_2'(d_1) + \beta r_2'(g_2)g_2'(d_1) = c'(d_1), \tag{4b}$$

$$\begin{aligned}[d_1^n] \quad & r_1'(d_1) + \beta r_2'(d_1) + \beta r_2'(d_2)d_2'(d_1) + \beta r_2'(g_2)g_2'(d_1) \\ & + r_1'(g_1)g_1'(d_1) = c'(d_1)\end{aligned} \tag{4c}$$

For defense, the same first order condition holds in each case.[12]

$$[g_1] \quad r_1'(g_1) = e'(g_1) \tag{4d}$$

Moral hazard arises both within and across periods. Within periods, devel-

[11] I can accommodate flood risk uncertainty with a shock realized between periods one and two. Period-one conditions would be in expectation of the shock, with direct commitment to specific actions. Period-two conditions would be conditional on the shock, with commitment to a contingency plan specifying actions under each possible realization of the shock.

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

opers exploit the government. Both $r_2'(g_2)g_2'(d_2) > 0$ in period two (equation 3a) and $r_1'(g_1)g_1'(d_1) > 0$ in period one (equation 4c) prompt over-development that forces over-defense. Across periods, current developers exploit the future government. In period one, $r_2'(d_2)d_2'(d_1), r_2'(g_2)g_2'(d_1) > 0$ (equation 4c) prompts current over-development that forces future over-defense. Similarly, a politically myopic current government exploits the future government, as the same terms (equation 4b) lead to current over-investment given uninternalized future costs.

Furthermore, development has persistent effects. On one hand, this persistence creates lock-in at the coast. Over-development in period one prompts over-defense in period two, as the government seeks to protect sunk $d_1 > d_1^*$.[13] The result is over-development in period two, even when the period-two government has commitment power. On the other hand, this persistence allows the current government to help future governments. In period one, $r_2'(g_2)g_2'(d_1) > 0$ (equation 4a) induces under-defense that reduces moral hazard and the resulting over-defense in period two. The current government moves before future developers and thus shapes their actions.

As before, commitment avoids over-development. Commitment to first-best defense (g_1^*, g_2^*) eliminates moral hazard, as do taxes and restrictions targeting first-best development (d_1^*, d_2^*). This commitment requires the government to resist its static incentives – as well as lobbying – not only in period one, but also in period two. More generally, commitment avoids over-development only if it holds over the long run. Limited commitment is insufficient. Even if the current government has commitment power, over-development proceeds if a future government does not. This over-development then forces the current government to over-defend despite its commitment power. Multi-period dynamics thus greatly complicate commitment.

Alternative policies constrain long-run development more indirectly. Lower demand reduces developers' returns from over-defense and thus lessens moral hazard. The government can lower coastal demand by relocating residents with direct mandates, migration subsidies, or improving non-coastal amenities. Such policies may be more politically feasible over the long run than direct attempts to regulate or punish development, and they can have persistent effects even if implemented temporarily.

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

Capital destruction can also constrain long-run development. A smaller stock of development reduces the need for defense, which lowers new development. But it also increases the extent to which new development drives defense, thereby raising moral hazard. Appendix A considers extensions.

4 Empirics

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

4.1 Framework

The theory of section 3 frames the empirical analysis. Consider components $r(d, g)$, $c(d)$, and $e(g)$ of social welfare for development d and defense g, and let $r(d, g)$ be $r(d, f(g))$ given defense that increases residential value by reducing flooding $f(g)$. The sections that follow construct empirical analogues for each term. I obtain $r(d, f(g))$ by estimating a spatial model of residential demand, and costs $c(d)$ of development by estimating a dynamic model of developer supply. Sections 5 and 6 describe these economic models that characterize how flooding affects urban development in equilibrium. A hydrological model specifies how defense reduces flooding $f(g)$, and engineering estimates yield the costs $e(g)$ of defense. Section 7 describes these benefits and costs of government intervention.

4.2 Data

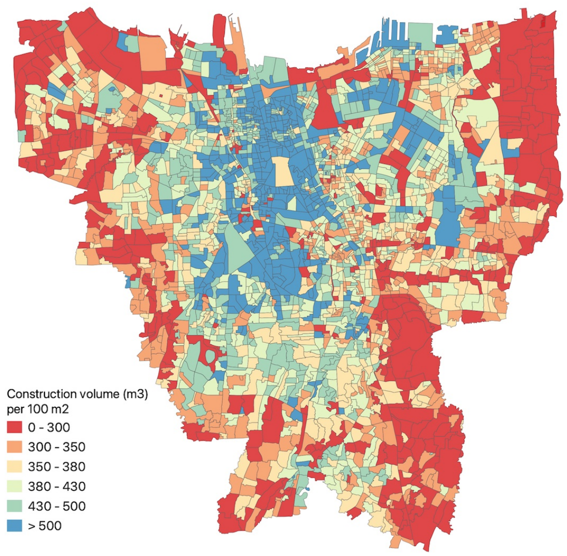
I compile high-resolution spatial data on building construction, populations, real estate values, and flooding across Jakarta at the tract level and below. Jakarta consists of five districts (*kota*), 44 sub-districts (*kecamatan*), 267 neighborhoods (*kelurahan*), and 2,722 tracts (*rukun warga*).[14] Each tract contains around 4,000 people. Figure 3 illustrates the data, and appendix B provides additional detail.

The Global Human Settlement Layer measures building construction and populations across Jakarta (GHSL 2022). It does so at the 100m grid cell level every

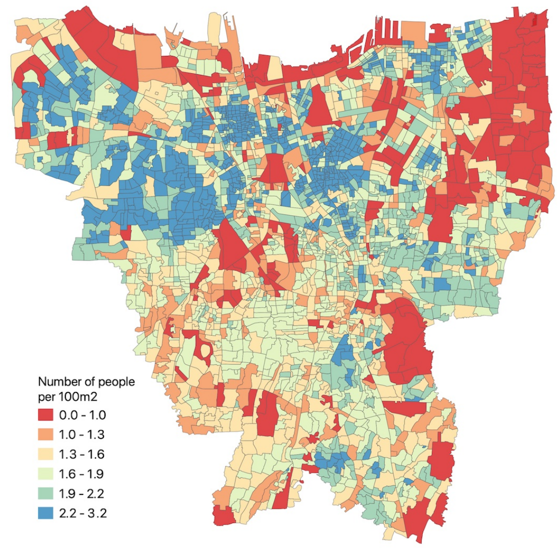
[14] I focus on Jakarta proper, although the empirical analysis accounts for movement across the broader metropolitan area. I exclude the islands of *Kepulauan Seribu* district.

Figure 3: Data (2015)

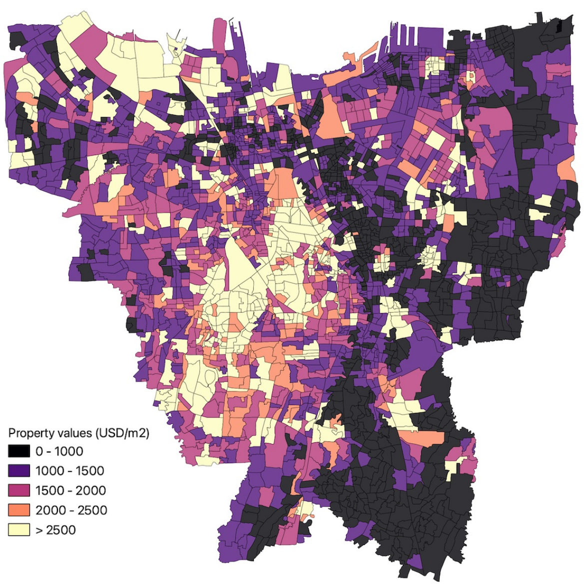
(a) Building construction



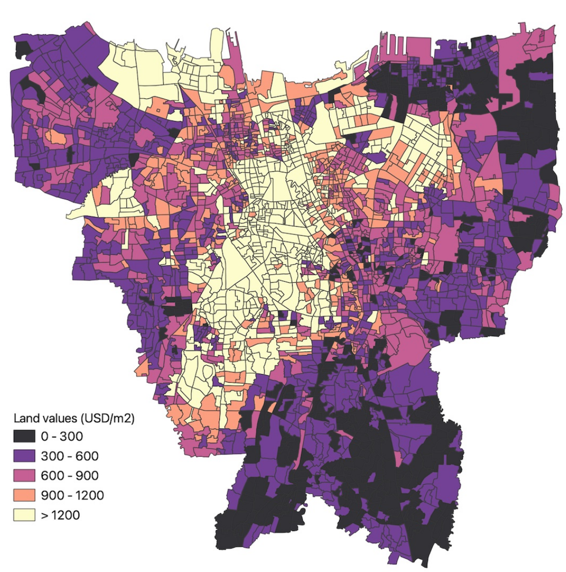
(b) Population



(c) Property value



(d) Land value



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

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

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

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

Flooding data 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 use these data to compute measures of flood frequency and depth. I do so by tract as follows. For flood frequency, I count the number of months in each year with flooding, then I average across years. Figure 1 maps these frequencies. For flood depth, I sum over the monthly flood depths in each year, then I again average across years.

4.3 Historical government intervention

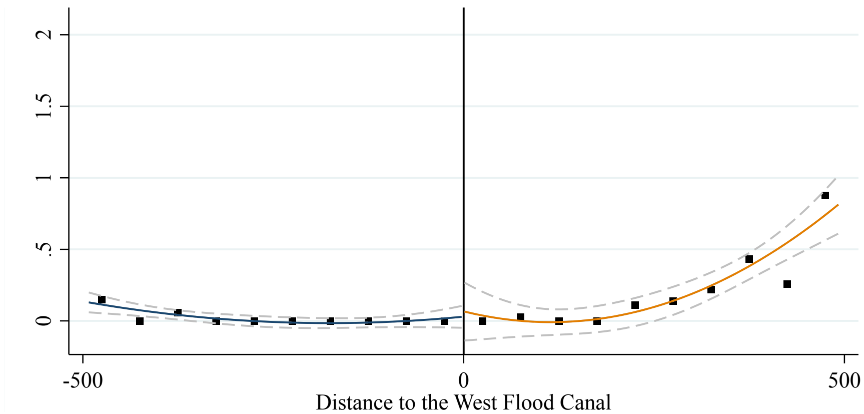
I consider whether historical investments in flood protection led to higher levels of land development. The opening of the West Flood Canal in 1918 allows me to study this dynamic over the last century, with historical maps from the Dutch colonial era providing measures of land development both before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

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. I restrict attention to cells in the vicinity of the canal, dropping those located directly on its boundary, and I plot land development relative to distance to the canal. Figure 4 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 B shows the associated regression table and 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.

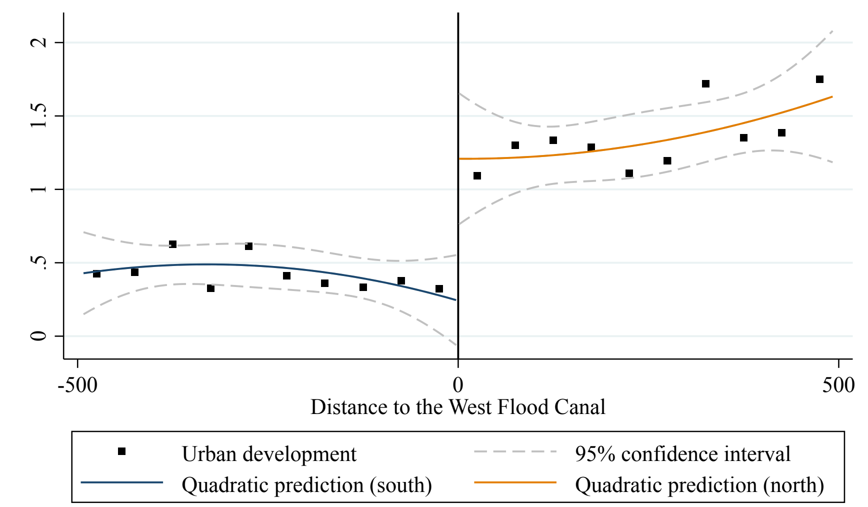
This spatial discontinuity approach is subject to several potential concerns. First, the government may have anticipated future land development when placing the canal. But it seems difficult to target development 30 years in the future, and also to target finely enough to distinguish among 100m cells.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

Figure 4: Land development and the West Flood Canal

(a) Before (1910)



(b) After (1945)



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

north and south over the 10km stretch of canal that I study.[15]

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

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

$$U_{ijk} = \underbrace{-\alpha r_k - \phi f_k + \xi_k}_{\delta_k} - \tau m_{jk} + \epsilon_{ijk} \tag{5}$$

for rent r_k, flooding f_k, amenity ξ_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. Distance introduces spatial dependence.[16] Residential demand sums over origins given populations n_j and choice probabilities p_{jk}^{res}. Development demanded in each location is thus

$$D_k^{\text{res}} = \sum_j n_j p_{jk}^{\text{res}} \varphi, \quad p_{jk}^{\text{res}} = \frac{\exp(\delta_k - \tau m_{jk})}{\sum_{\hat{k}} \exp(\delta_{\hat{k}} - \tau m_{j\hat{k}})} \tag{6}$$

given floor space φ per resident. Moving inland is costly because it abandons high-amenity tracts and incurs migration costs. Future work can incorporate firms locating over space as a means of endogenizing amenities. 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 the endogeneity of rents by instrumenting with ruggedness as a cost shifter. I focus on residential choice within the core of

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

Jakarta, but I include the option of a location that aggregates over the periphery.[17] Total metropolitan population, which includes both core and periphery, evolves exogenously. I take rents to be mortgage payments on observed property values.

Estimation follows Berry (1994) and Berry et al. (1995), except that I integrate over origins instead of over a broader set of demographics. I estimate $\theta = (\theta_1, \theta_2)$ for $\theta_1 = (\alpha, \phi)$ and $\theta_2 = \tau$. First, fixing θ_2, I match observed and model-implied populations by computing $\delta = \{\delta_k\}$ by contraction mapping.[18] Suppressing dependence on data (n, m), equation 6 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. Population growth rate λ, which I impose uniformly across locations, augments 2015 populations such that origin and destination populations balance.

$$\lambda \left(\sum_j n_j^{2015} \right) = \sum_k n_k^{2020}$$

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

$$\xi_k = \delta_k + \alpha r_k + \phi f_k$$

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

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

Fourth, I search over θ_2 to minimize $Q(\theta)$.

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

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

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

Table 1: Residential demand estimates

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

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

5.3 Estimates

Table 1 presents the demand estimates. Demand is decreasing in rents, as is consistent with downward-sloping demand. Addressing the endogeneity of rents is crucial, as I use the rent coefficient to monetize welfare in counterfactuals. The first stage shows that ruggedness acts as a significant cost shifter, increasing rents by raising construction costs, and a large F-statistic demonstrates the strength of the instrument. Furthermore, demand is decreasing in flooding, which represents a disamenity. This demand system thus ties welfare to flooding. In particular, the flooding coefficient characterizes the extent to which 2020 residential choices reflect realized flooding from 2013 to 2020. I use this coefficient to compute welfare in counterfactuals with sea walls that decrease flooding.

I focus on flooding rather than flood risk to mitigate bias from misperception of risk, which even for experts is difficult to quantify. I instead allow residents to respond directly to eight years of flooding history that is both observed and indicative of underlying flood risk. This flooding also captures relatively high tail risk, as it includes major flooding in 2013 and 2020 with returns periods of 30 and 50 years. Even so, welfare effects will be biased if residents respond suboptimally to flooding, perhaps because of incorrect beliefs over its negative effects. But it is residents' actual – not optimal – responses to flooding that are relevant for rents and thus developer behavior. The same is arguably true for votes and thus government behavior. Moreover, disentangling residents' beliefs and preferences remains difficult in general.

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

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

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 atomistic 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, with time to build of one period. Development and land follow laws of motion

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

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.

I explicitly model the extensive-margin choice to develop or not, which lumpiness makes a key margin of variation in the data.[19] The ex-ante value function is

$$V(D_{ikt}, L_{ikt}, w_{kt}) = r(D_{ikt}, w_{kt}) + \mathbb{E}[\max_{d\in\{0,1\}} \{v^d(D_{ikt}, L_{ikt}, w_{kt}) + \epsilon^d_{ikt}\}]. \tag{7}$$

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 $v^1_{kt}(\cdot) \equiv v^1(\cdot, w_{kt})$, $V_{kt+1}(\cdot) \equiv V(\cdot, w_{kt+1})$, and $\mathbb{E}_{kt}[\cdot] \equiv \mathbb{E}[\cdot|w_{kt}]$, the choice-specific conditional value functions are

$$v^1_{kt}(D_{ikt}, L_{ikt}) = \max_{d,\,\ell} \big\{ - c_{kt}(d, \ell) + \beta \mathbb{E}_{kt}[V_{kt+1}(D_{ikt} + d, L_{ikt} - \ell)]\big\}, \tag{8a}$$

$$v^0_{kt}(D_{ikt}, L_{ikt}) = \beta \mathbb{E}_{kt}[V_{kt+1}(D_{ikt}, L_{ikt})], \tag{8b}$$

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.

$$r_{kt}(D) = R_{kt}D, \quad c_{kt}(d, \ell) = \frac{1}{2}\psi d^2 + \frac{1}{2}\omega\left(\frac{d}{\ell}\right)^2 + d x_{kt}\gamma + \varepsilon_{kt} \tag{9}$$

[19] In the data, most cells in a given period contain zero development. Larger cells would contain fewer zeros, but also obscure spatial heterogeneity.

Revenues depend on completed development D and rents R_{kt}, while 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. Unobserved ε_{kt} and idiosyncratic $\epsilon_{ikt} = \epsilon^1_{ikt} - \epsilon^0_{ikt}$ are fixed costs that influence neither floor space nor land use, which by equation 8a satisfy conditions

$$[d_{kt}] \quad \frac{\partial}{\partial d} c_{kt} = \frac{\partial}{\partial d} \beta \mathbb{E}_{kt}[V_{kt+1}], \qquad [\ell_{kt}] \quad \frac{\partial}{\partial \ell} c_{kt} = \frac{\partial}{\partial \ell} \beta \mathbb{E}_{kt}[V_{kt+1}]. \tag{10}$$

Flow costs are passed onto residents and thus subsumed into rents. Developers seek high rents and low construction costs.

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

$$D^{\text{dev}}_{kt+1} = D_{kt} + d_{kt} p^{\text{dev}}_{kt}, \quad p^{\text{dev}}_{kt} = \frac{\exp\{v^1_{kt}(D_{ikt}, L_{ikt})\}}{\exp\{v^1_{kt}(D_{ikt}, L_{ikt})\} + \exp\{v^0_{kt}(D_{ikt}, L_{ikt})\}}. \tag{11}$$

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 that clear markets for development in each location k and period t.

$$D^{\text{res}}_{kt} = D^{\text{dev}}_{kt}$$

for demand D^{res}_{kt} and supply D^{dev}_{kt}. 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 resident demographics, which shift local demand for development. Inverting equation 11 and substituting equations 8,

$$\ln p^{\text{dev}}_{kt} - \ln\big(1 - p^{\text{dev}}_{kt}\big) = -c_{kt}(d_{kt}, \ell_{kt}) + \beta \mathbb{E}_{kt}[V_{kt+1}(D_{ikt} + d_{kt}, L_{ikt} - \ell_{kt}) - V_{kt+1}(D_{ikt}, L_{ikt})].$$

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.

$$\beta\mathbb{E}_{kt}[V_{kt+1}(D_{kt+1}, L_{kt+1})] = P^D_{kt}D_{kt+1} + P^L_{kt}L_{kt+1} \tag{12}$$

for property prices P^D_{kt} per unit of floor space and land prices P^L_{kt} per unit of land. Market value is priced after new development and land use (d_{kt}, ℓ_{kt}). It thus depends on current-period prices (P^D_{kt}, P^L_{kt}), which capture current-period expectations, and next-period holdings (D_{kt+1}, L_{kt+1}), which condition on development in progress. I substitute to eliminate continuation values, which greatly simplifies estimation.

$$\ln p^{\text{dev}}_{kt} - \ln\big(1 - p^{\text{dev}}_{kt}\big) = -c_{kt}(d_{kt}, \ell_{kt}) + P^D_{kt}d_{kt} - P^L_{kt}\ell_{kt}$$

Prices act as numeraire. Applying equations 9 and 10 gives estimating equation

$$\ln p^{\text{dev}}_{kt} - \ln\big(1 - p^{\text{dev}}_{kt}\big) = \frac{1}{2\psi}\bigg(- x_{kt}\gamma - \frac{P^L_{kt}}{h_{kt}} + P^D_{kt}\bigg)^2 - \frac{1}{2}\omega h^2_{kt} - \varepsilon_{kt}. \tag{13}$$

I estimate equation 13 with nonlinear instrumental variables. The endogeneity problem is that unobserved costs ε_{kt} affect development supply, which in turn affects property and land prices (P^D_{kt}, P^L_{kt}).[20] Estimation thus leverages instruments Z and moment condition $\mathbb{E}[Z\varepsilon(\theta)]$. I obtain $\varepsilon(\theta)$ as follows. First, I compute the left-hand side of equation 13 by calculating probabilities p^{dev}_{kt} of new development from the data, applying a frequency estimator then smoothing nonparametrically across bins. I do so offline. Second, for candidate parameter values θ, I compute the right-hand side in terms of ε_{kt} with parameters θ and data $(x_{kt}, h_{kt}, P^L_{kt}, P^D_{kt})$. I do so taking heights h_{kt} as given.[21] The main data requirement is thus property and land values, which are available in many urban settings (but perhaps not rural settings). Third, I difference the left- and right-hand sides to solve for ε_{kt}.

[20] 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.

[21] I can endogenize h_{kt} with $d_{kt} = \frac{1}{\psi}(-x_{kt}\gamma - P^L_{kt}/h_{kt} + P^D_{kt})$, $h_{kt} = (P^L_{kt}d_{kt}/\omega)^{1/3}$, and $\ell_{kt} = d_{kt}/h_{kt}$, as by equations 10. Solving in (d, ℓ, h) gives $h_{kt}(\theta)$. I then require two instruments for (P^D_{kt}, P^L_{kt}).

The key assumption for estimation is that equation 12 holds, such that market prices capture expected future profits. First, I require efficient markets that push prices toward expectations. In such a setting, 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. Estimation accommodates inefficiencies like thin markets and transaction costs by attributing them to unobserved ε_{kt}, but counterfactuals will hold these terms fixed. Second, I require atomistic developers. If individual developers do not affect prices, then observed prices capture continuation values. But if large developers depress prices, then observed prices do not. Continuation values must be computed directly, and I lose the benefit of appealing to price data.

My approach remains flexible on expectations themselves. In particular, I can accommodate expectations consistent with empirical findings that flood risk does not fully capitalize into real estate prices (Hino and Burke 2021, Bakkensen and Barrage 2022). I begin by noting that such findings do not necessarily imply irrational expectations. If developers accurately anticipate government intervention, then risk does not fully capitalize into prices – even with perfect foresight over future flooding. Indeed, allowing for expectations over government intervention is crucial in my context. At the same time, I can also accommodate irrational expectations, such as those arising from behavioral biases and hysteresis. My dynamic model is one in which prices reveal expectations of future rents, which forward-looking developers anticipate collecting. An isomorphic model casts prices as revenues from selling development outright, with developers making static decisions to construct and sell immediately. Market expectations may be irrational, but developers take the resulting prices as given and develop accordingly.

An alternative is the Euler conditional choice probability approach, applying methods from Scott (2013) that I build on in previous work (Hsiao 2022). The intertemporal comparison between developing today and tomorrow implies an estimating equation that I derive in appendix C. I highlight several differences with my approach. The Euler approach requires long-lived developers that control land for multiple periods and choose the timing of development, while I can have short-lived entrants that buy land, develop, and sell immediately. It cannot accommodate depreciating development, while I allow for depreciation through its capitalization into prices. It requires at least two periods of data on new development, while I need only one. More broadly, it emphasizes differences between periods t and $t+1$, while I emphasize differences between property and land values.

A broader comparison considers two other approaches for dynamic discrete choice estimation. The full-solution approach, following the nested-fixed point algorithm of Rust (1987), repeatedly computes continuation values. It is thus computationally intensive and requires specifying expectations explicitly. Two-step approaches, as reviewed in Ackerberg et al. (2007), simplify computation by estimating continuation values nonparametrically from the data, then estimating model parameters.[22] However, expectations remain specified.[23] The Euler approach simplifies computation and affords flexibility over expectations. It does so by appealing to finite dependence, as in Arcidiacono and Miller (2011), such that continuation values and long-run expectations difference out. It requires rational expectations but does not specify expectations. My approach simplifies computation and allows full flexibility over expectations. I can accommodate irrational expectations – at least during estimation – because with price data I measure expectations directly.

At the same time, it remains difficult to relax the assumption of atomistic agents. For the Euler approach, large developers influence the evolution of the economy, causing finite dependence to fail. For my approach, large developers change prices from those observed in the data. Market power also greatly increases the computational burden of solving the model for counterfactuals. However, offsetting mechanisms may limit bias: under-development arises from typical price-setting incentives, while over-development arises as market power increases developers' influence on government intervention. I thus abstract from market power in the baseline approach, but I can accommodate it in a reduced-form way in assessing robustness.[24]

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

[23] And my non-stationary model does not enter the recurrent class of states needed for the first step.

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

7 Government

Government commitment, as well as the benefits and costs of defense, determine the extent of government intervention. Defense is durable and follows

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

7.1 Commitment

Commitment dictates the government's ability to resist static incentives to deviate from dynamically optimal strategies. I consider a range of scenarios. Under full commitment, the government makes an upfront plan for defense over time by maximizing jointly over defense in each period. It then adheres to this plan in subsequent periods. Under no commitment, the government instead pursues sequential static optimization, choosing defense in each period while taking prior development and defense as given. Limited commitment lies between these extremes: the government plans defense upfront and acts accordingly during the commitment period, after which it acts with no commitment.

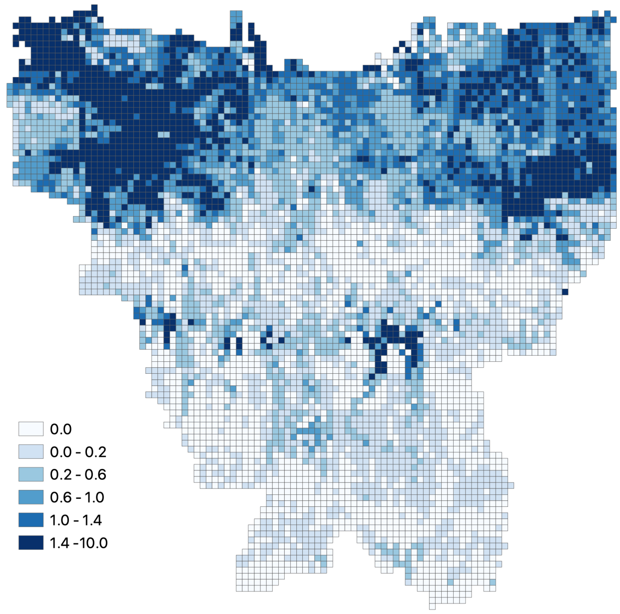
Politics affect the government's objective function under limited commitment. A forward-looking government chooses defense to maximize social welfare from current to terminal period. By contrast, a politically myopic government maximizes social welfare during its administration. It also considers future social benefits, which it claims credit for providing, but it ignores future social costs, which are borne by future administrations. I focus on politics for limited commitment, as full commitment demands forward-lookingness and no commitment involves its own form of myopia.

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

broader dynamic game, but each retains computational tractability.

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



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

and at the tract level. As input data, I use rainfall, elevation, slope, and distances to major rivers, minor rivers, and the coast. I train a range of machine learning models and find that a histogram gradient boosting decision tree performs best. I impose monotonicity constraints on distance to major rivers and elevation, which help to reduce overfitting by applying basic physical properties without the complexity of modeling the full physical system. Appendix C describes this procedure in detail.

The trained model allows me to simulate how a sea wall would affect flooding across Jakarta. Figure 5 shows the impact of a 5m sea wall, which I simulate by raising the elevation of the city relative to sea level. The predictions align with intuition. The coastal north benefits most from the sea wall, with especially large reductions in flooding in low-elevation areas. Some parts of the high-elevation south also benefit, as greater drainage in the north alleviates flooding near river banks in the south. Indeed, the machine learning model captures this interaction without an explicit model of the complex physical processes that determine river drainage. I ignore existing sea wall protections, which a 2020 government report calls “very poor” (NCICD 2020).[25]

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. Higher supply decreases rents, which in equilibrium balance demand and supply responses.

7.3 Costs

I obtain engineering cost estimates from government reports on Jakarta's planned sea wall, which runs onshore along the coast and offshore through Jakarta Bay (NCICD 2014, 2020). Onshore length is 60 km 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.[26] 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 5 would require only 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 approximately $11M per meter of height

[25] “Currently, the level of flood protection on existing coastal and river embankments is very low.” (“*Saat ini, tingkat perlindungan banjir pada tanggul pantai dan sungai eksisting sangat rendah.*”)

[26] 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.

and kilometer of length. For the 5m sea wall discussed above, this unit cost of \$11M implies a total cost of \$12B.[27] Lenk et al. (2017) also find that cost uncertainty is well characterized by a factor of three, which I consider in assessing robustness.

8 Counterfactuals

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

8.1 Simulations

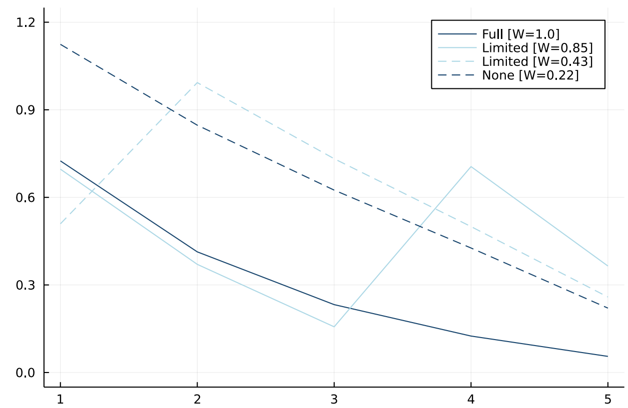
I simulate coastal development and defense over five periods. Figure 6a considers a forward-looking government. Full commitment gives the first best, while no commitment induces moral hazard and over-development in each period. Limited commitment involves under-development during the commitment period, offsetting the over-development that follows. Figure 6b considers a politically myopic government. Limited commitment does less to reduce over-development, as the benefits of commitment are undercut by the failure to internalize future costs. Figure 6c considers relocated demand that reduces coastal residential value by 25%. Moving the political capital from Jakarta might lead to such a reduction, as could other policies like inland investments or migration subsidies. Lower demand reduces developers' gains from exploiting the government, lessening moral hazard and reducing over-development under non-commitment. Appendix D presents the corresponding patterns of government defense.

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

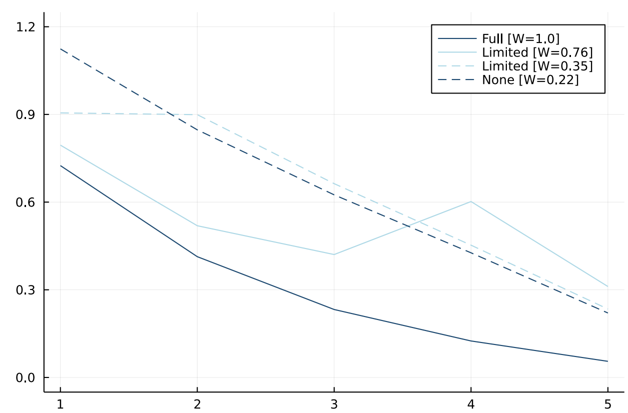
[27] Offshore above-water and total heights are 10m and 26m, relative to 8m and 24m as planned.

Figure 6: New coastal development over time (d_t)

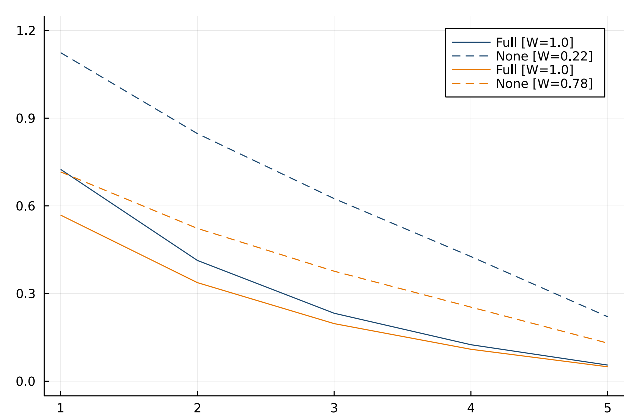
(a) Forward-looking government



(b) Political myopia



(c) Relocating demand



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

Table 2: Welfare effects

	L	W Baseline	W Relocating demand
Full commitment	5	1.00	1.00
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%.

mand greatly reduces the commitment problem, raising no-commitment welfare to 78% of first-best welfare and scaling limited-commitment outcomes proportionally.

9 Conclusion

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

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APPENDIX

A Theory

Extensions

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

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

Finally, I consider durable defense. In this case, defense investments are largely upfront: if defense is optimal tomorrow, then it is optimal today because it protects development for an additional period. Future defense investment are thus minimal under the baseline assumptions, particularly if defense depreciates slowly. In reality, however, rising sea levels increase flood risk over time and prompt continued investment in defense. Similarly, rising rents and falling costs prompt continued development, as do convex costs that force development to be spread over time. Non-durable defense thus captures the repeated government intervention observed in the richer model, as well as in practice.[28]

Anecdotal evidence

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

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

Figure A1: Co-determination of development and defense

(a) Development given defense

(b) Defense given development

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

Table B1: Data sources

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

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

B Data

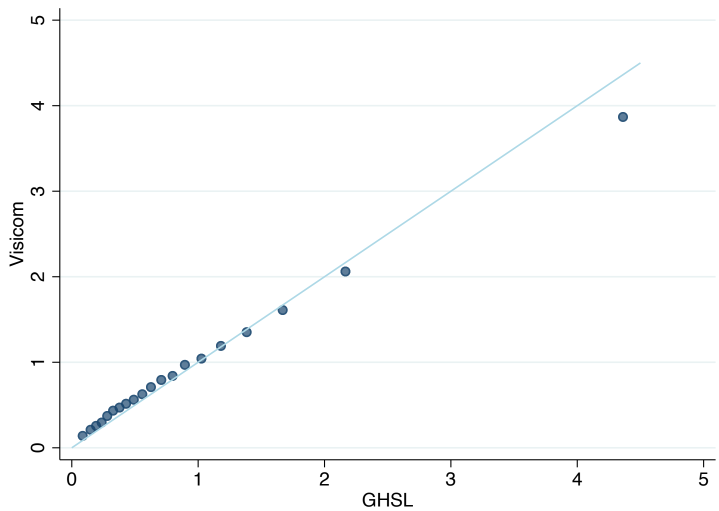
Table B1 lists data sources. This section details data construction and validation.

Building construction

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

defense eliminates it even in the two-period case.

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



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

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

Property values

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

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

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

Table B2: Geocoding property listings

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

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

meter by dividing prices by floor space, dropping the 1% of listings without information on prices or building areas. I collapse listings with identical addresses – primarily apartment listings within complexes – into single observations by taking means. I then aggregate to the tract level as follows. For the 70% of tracts with more than five observations, I take the mean. For the 30% of tracts with less than five observations, I compute an inverse-distance-weighted mean of nearby observations.[29] I thus obtain property values for 2022.

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

Historical land development

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

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

[29] 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.

Table B3: Dutch colonial maps

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

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

Figure B2: Ground control points for georeferencing

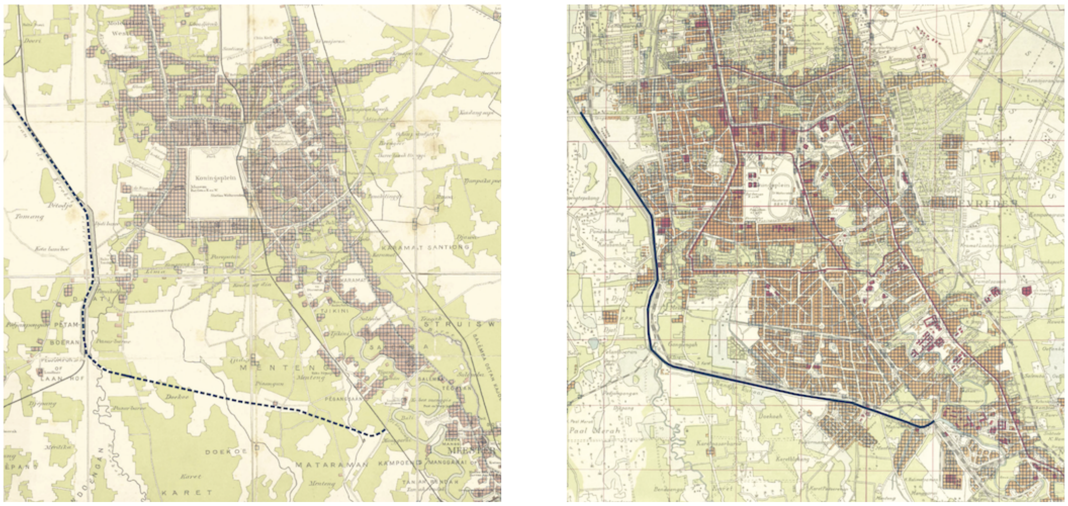
(a) Pre-1918 maps

(b) Post-1918 maps

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

Figure B3: Land development and the West Flood Canal

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



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

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

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

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

Table B4: Land development at the canal boundary by year

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

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

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

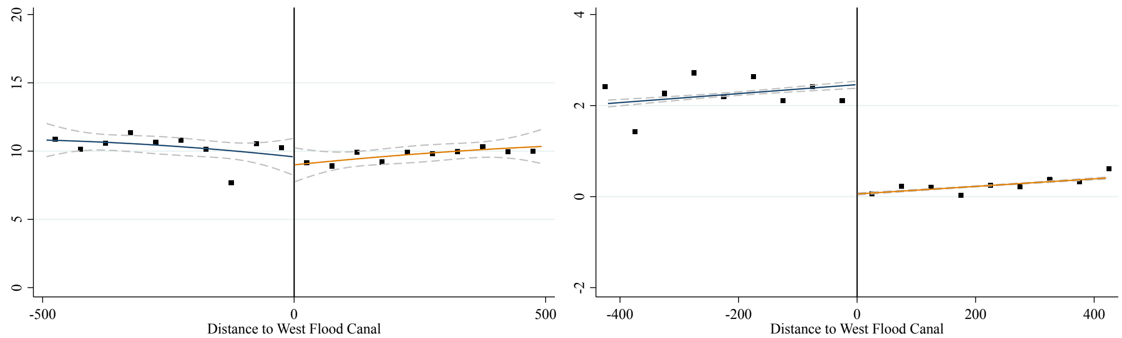
Table B4 draws on data from the full panel to measure the discontinuity in each available year. For cell c and year t, the specification is

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

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

Figure B4: Validating the spatial regression discontinuity design

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

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

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

C Estimation

Euler conditional choice probabilities

The Euler approach compares two sequences of actions: $(d_{kt}, 0)$ and $(0, d_{kt})$. The first develops d_{kt} today and zero tomorrow, while the second develops zero today and d_{kt} tomorrow. Each involves land use ℓ_{kt}. Intuitively, developing tomorrow reduces upfront costs given discounting, but it also delays the arrival of rental revenue. Choice-

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

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

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

(b) Building construction (m^3)

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

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

specific conditional value functions are

$$
\begin{aligned}
v^1_{kt}(D_{ikt}, L_{ikt}) &= -c_{kt}(d_{kt}, \ell_{kt}) + \beta \mathbb{E}_{kt}[R_{kt+1}(D_{ikt} + d_{kt}) - \ln\big(1 - p^{\text{dev}}_{kt+1}\big)] \qquad (14a)\\
&\quad + \beta^2 \mathbb{E}_{kt}[V_{kt+2}(D_{ikt} + d_{kt}, L_{ikt} - \ell_{kt})],\\
v^0_{kt}(D_{ikt}, L_{ikt}) &= \beta \mathbb{E}_{kt}[R_{kt+1} D_{ikt} - c_{kt+1}(d_{kt}, \ell_{kt}) - \ln p^{\text{dev}}_{kt+1}] \qquad (14b)\\
&\quad + \beta^2 \mathbb{E}_{kt}[V_{kt+2}(D_{ikt} + d_{kt}, L_{ikt} - \ell_{kt})]\\
&\quad + \frac{1}{2}\beta \mathbb{E}_{kt}[c''_{kt}(d_{kt})(d_{kt+1} - d_{kt})^2 + c''_{kt}(h_{kt}(\ell_{kt}))(h_{kt+1}(\ell_{kt+1}) - h_{kt}(\ell_{kt}))^2].
\end{aligned}
$$

The first and third lines impose the actions of interest to equations 8. 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.

$$
\begin{aligned}
V_{kt}(D_{ikt}, L_{ikt}) - R_{kt} D_{ikt} &= v^1_{kt}(D_{ikt}, L_{ikt}) - \ln p^{\text{dev}}_{kt} = v^0_{kt}(D_{ikt}, L_{ikt}) - \ln\big(1 - p^{\text{dev}}_{kt}\big),\\
v^1_{kt}(D_{ikt}, L_{ikt}, d, \ell) &= v^1_{kt}(D_{ikt}, L_{ikt}) - \frac{1}{2}c''_{kt}(d_{kt})(d_{kt} - d)^2 - \frac{1}{2}c''_{kt}(h_{kt})(h_{kt}(\ell_{kt}) - h(\ell))^2
\end{aligned}
$$

for $v^1_{kt}(D_{ikt}, L_{ikt}) = \max_{d,\ell}\{v^1_{kt}(D_{ikt}, L_{ikt}, d, \ell)\}$. The first line is a special case of Arcidiacono and Miller (2011) Lemma 1, and the second line is as derived in Hsiao (2022). Inverting equation 11 and substituting equations 14, continuation values V_{kt+2} cancel under finite dependence. For $\Delta X_{kt} = X_{kt} - \beta X_{kt+1}$ and $\tilde{X}_{kt} = X_{kt} - X_{kt+1}$,

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

given expectational errors η_{kt}, which by rational expectations are mean zero (correct on average) and orthogonal (use all in information set $\mathcal{J}_{kt}$). This assumption allows me to 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 the years 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 using the slope algorithm of the QGIS raster terrain analysis toolkit, which computes slope in degrees as the angle of terrain inclination. I compute river and coastal distances with OpenStreetMap shapefile data, which distinguish major rivers from streams.

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

I consider a range of models and choose the one with the best fit. Table C1 presents the results. Ensemble methods like random forests, gradient boosting decision trees, and histogram gradient boosting decision trees perform best, as measured

Table C1: 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.

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

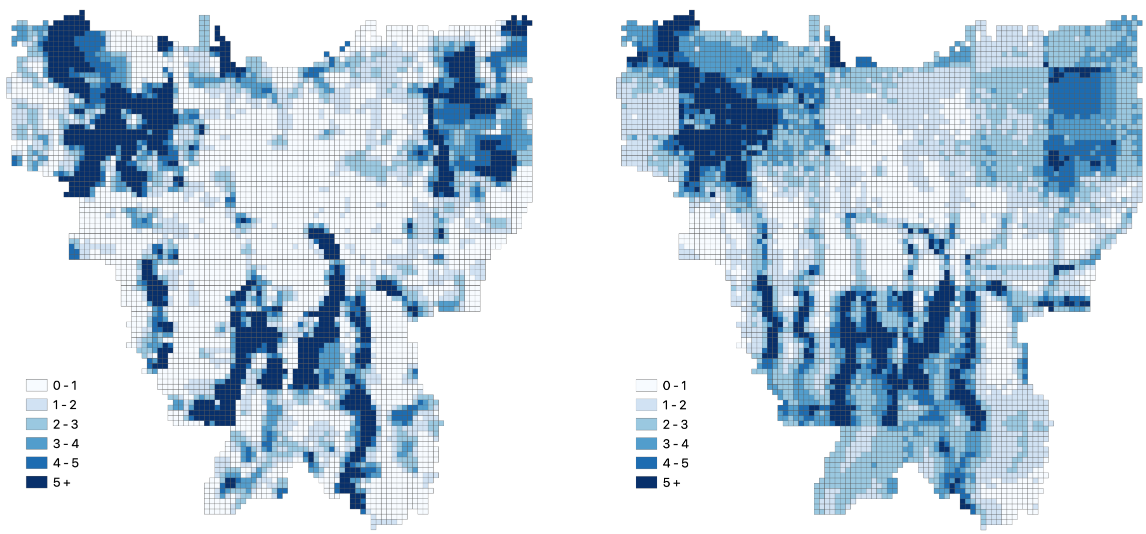
D Counterfactuals

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

Figure C1: Model fit (flood frequency)

(a) Observed

(b) Predicted



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

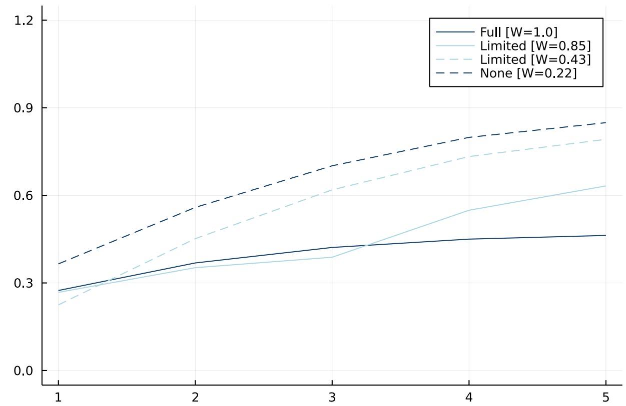
Table C2: Feature importance

Feature	Importance
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

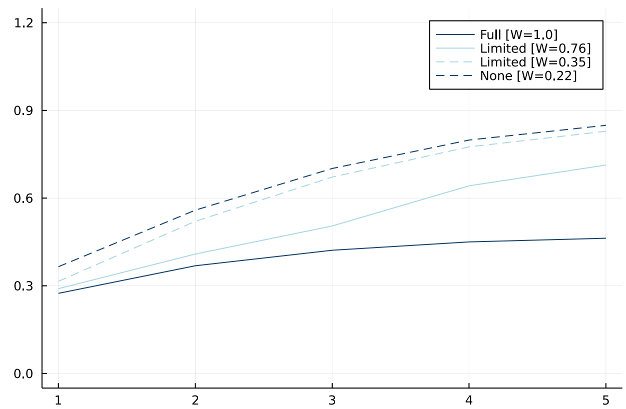
Permutation feature importance quantifies the dependence of model fit on a given feature. The table presents this measure for a histogram gradient boosting decision tree with monotonicity constraints on distance to major rivers and elevation.

Figure D1: Coastal defense over time (g_t)

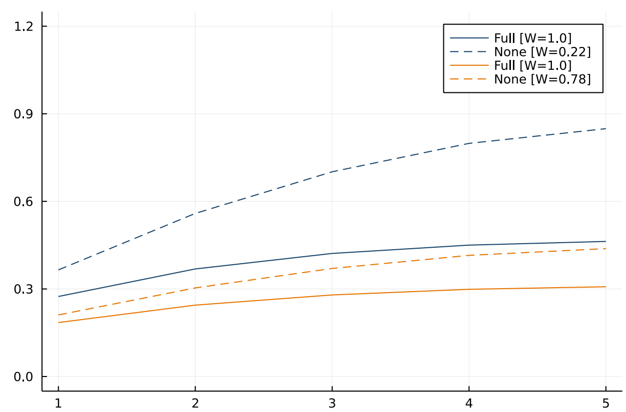
(a) Forward-looking government



(b) Political myopia



(c) Relocating demand



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