Sea Level Rise and Urban Adaptation in Jakarta

Allan Hsiao

Stanford University

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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 by creating coastal moral hazard. I quantify this force with a dynamic spatial model of urban development and flooding. I show that moral hazard generates coastal lock-in by delaying inland migration, and I evaluate policies for reducing this friction.

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1 Introduction

Sea level rise is a major threat to economic development. Nearly one billion people live in low-elevation coastal zones with direct exposure to coastal catastrophe (IPCC 2019). This threat is growing quickly in Southeast Asia, where land subsidence greatly accelerates the experience of sea level rise (Nicholls et al. 2021). Particularly vulnerable are the 32 million residents of Jakarta, a megacity on pace to be the world's most populous by 2030 (Euromonitor 2018).

Jakarta faces frequent flooding with $300 million in annual damages, which will only worsen as sea levels continue to rise (Budiyono et al. 2015). The Indonesian government has responded with a proposed sea wall at up to $40 billion in cost. I study how government intervention complicates long-run adaptation by creating moral hazard. The government tends to protect coastal development ex post despite not wanting to ex ante, inducing over-development that forces 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.[1] I formalize the commitment problem in the context of sea level rise, and I show how it limits adaptation over time by generating coastal lock-in.

I begin by documenting how development responded to historical intervention in Jakarta. I study the West Flood Canal, which was completed in 1918, and I measure historical land development by digitizing Dutch colonial maps from 1887 to 1945. The canal diverts a major river around the city center, protecting areas to its north but not to its south. Thus, while the north and south were similar before the canal, the north experienced less flooding after the canal's completion. I apply a spatial regression discontinuity design at the canal boundary in the spirit of Almond et al. (2009), and I find that intervention induced increased development.

I study how this response creates a commitment problem for government inter-

[1] 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."

vention, focusing on Jakarta's planned sea wall. I do so quantitatively by combining a dynamic spatial model of urban development with a hydrological model of flooding. Developers and residents make investment and location decisions with flooding in mind. Residential demand is spatial, as individuals make location decisions over where to live. Developer supply is dynamic, as forward-looking developers make sunk investment decisions in immobile buildings. Equilibrium rents clear markets for development, equalizing residential demand and developer supply in each period. The government intervenes with a sea wall, which reduces flooding at the coast.

Estimation leverages granular data on developers, residents, and flooding. I estimate residential demand by matching the spatial distribution of population in 2015. I address the endogeneity of rents by instrumenting with ruggedness as a supply shifter. 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). If markets are efficient, then property prices capture the stream of rents from developed buildings, and land prices capture the option value of undeveloped land. Prices thus reflect continuation values, inclusive of expectations over future flooding and intervention. I address the endogeneity of prices by instrumenting with residential amenities as demand shifters. Both demand and supply estimation boil down to simple linear regressions. Finally, I follow the frontier of the hydrological literature in training a machine-learning model with monthly, tract-level data on flooding from 2013 to 2020. A histogram gradient boosting decision tree fits the data well and offers sensible predictions for how sea wall construction decreases flooding across space.

Counterfactuals show that commitment facilitates adaptation. I define commitment as long-run planning for coastal defense, followed by adherence to the plan. Coastal regulation is equivalent if followed by enforcement. Full commitment achieves the first best – gradual managed retreat – with short-run costs but long-run gains. Non-commitment creates moral hazard and lock-in, consistent with coastal persistence to date (Vigdor 2008, Kocornik-Mina et al. 2020, Lin et al. 2024). Relative to the first best, new coastal development is twice as high in 2100 and three times as high in 2200, despite the threat of sea level rise. The resulting welfare losses are meaningful at roughly $15B.

Moral hazard also rationalizes the incomplete capitalization of flooding into real estate prices, as others have documented (Hino and Burke 2021, Bakkensen and Barrage 2022, Gourevitch et al. 2023). Real estate prices reflect private costs, but moral hazard forces defense at public cost. That is, real estate prices are not social welfare and need not capture flooding, even with perfect information about flooding. I show that model-implied prices under non-commitment match observed coastal land prices in 2015, suggesting that moral hazard drives current development. Projecting into the future, I find that moral hazard sustains high prices despite severe flooding and socially costly defense. By contrast, shutting down moral hazard and appealing to flood misperceptions alone requires unrealistic optimism to match observed prices.

I offer policy prescriptions for navigating moral hazard. Each cautions against evaluating the sea wall in a vacuum, either only in the short term or only at the coast. First, I recommend any feasible form of commitment. Limited commitment over the short run and delayed commitment over future periods each reduce moral hazard. Partial commitment is less effective than full commitment, but also less politically challenging. Second, I recommend an integrated policy approach. Inland investment lowers coastal demand, and managed aquifer recharge slows land subsidence.[2] Each complements sea wall construction by reducing moral hazard, as each reduces the returns to forcing defense. Thus, integrated policy minimizes the losses from non-commitment in settings where commitment is difficult. Current efforts for a new political capital are in line with this approach.

My main contribution is to quantify how endogenous government intervention limits adaptation to sea level rise. Adaptation blunts the consequences of sea level rise (Desmet et al. 2021, Castro-Vincenzi 2024, Balboni 2025, Gandhi et al. 2025) and of climate change more broadly (Barreca et al. 2016, Costinot et al. 2016, Bilal and Rossi-Hansberg 2023, Cruz and Rossi-Hansberg, Nath 2024). In particular, Desmet et al. (2021) show that inland migration can greatly reduce damages from coastal flooding. Government intervention complicates this narrative by displacing private investment in self-protection (Peltzman 1975, Kousky et al. 2006, Boustan et al. 2012, Annan and Schlenker 2015, Kousky et al. 2018, Baylis and Boomhower 2022, Fried 2022), creating moral hazard as in insurance markets (Coate 1995, Wagner 2022, Mulder 2024, Ostriker and Russo 2024). Endogenizing government intervention exacerbates moral hazard, as intervention spurs coastal investment that forces further

[2] Casanova et al. (2016) and Dillon et al. (2019) describe managed aquifer recharge technology.

intervention. The result is coastal lock-in at social cost, in contrast to the smooth inland transition of Desmet et al. (2021).

Methodologically, I estimate a model of industry dynamics in the tradition of Hopenhayn (1992) and Ericson and Pakes (1995), drawing on dynamic discrete choice methods from Hotz and Miller (1993) and Arcidiacono and Miller (2011). I build on Kalouptsidi (2014), who shows how to avoid computing continuation values, at least in estimation, by reading them from data. I show how this insight greatly simplifies estimation of dynamic land use models with data generally available in urban settings, where durable development generates important dynamics (Glaeser and Gyourko 2005, Murphy 2018). My approach allows for straightforward estimation, transparent identification, and flexible expectations. In incorporating geography, I also complement a growing literature that brings dynamics to spatial models (Desmet et al. 2018, Caliendo et al. 2019, Kleinman et al. 2023, Desmet and Parro 2025).

Finally, I provide quantitative estimates and recommendations for Jakarta, drawing on work in environmental studies that assesses current and future flood damages (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 urgency to questions of adaptation and potentially worsening existing inequality (Hsiao 2024c). The city foreshadows the future for most coastal populations by century's end, particularly as sea walls enter policy discussions worldwide.[3] Jakarta's challenges are the world's challenges.

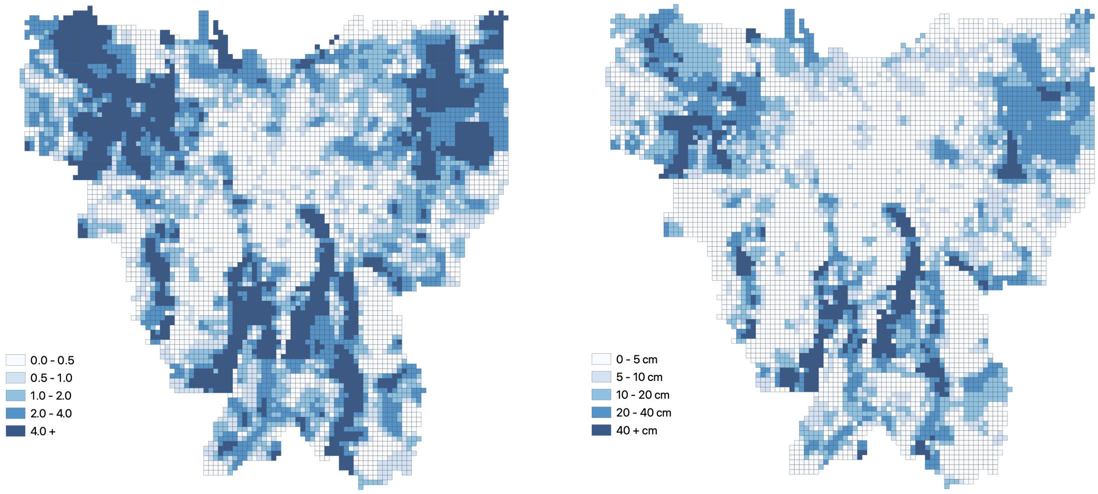
2 Background

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

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

Figure 1: Flooding (2013-2020)

(a) Frequency (b) Depth



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

from extreme rainfall, and so historical efforts have focused on river infrastructure that includes a westward canal (*Westerse Vaart*) in 1725, the West Flood Canal (*Banjir Kanal Barat*) in 1918, and the East Flood Canal (*Banjir Kanal Timur*) in 2002 (Octavianti and Charles 2019). Each complements a broader system of drains, pumps, reservoirs, and flood gates.

Coastal flooding adds significant additional risk in the coming decades. North Jakarta faces near total submersion by 2050, as sea level rise combines with rapid land subsidence. Official government plans describe scenarios of 3 to 5m of relative sea level rise by 2050, resulting from global mean sea level rise of 8mm per year and local land subsidence of 7 to 14cm per year (NCICD 2014). Groundwater extraction drives subsidence. Piped surface water accounts for only half of total water consumption, with the shortfall met by groundwater extraction that is largely unregistered and unregulated (Taftazani et al. 2022). Water demand continues to rise with a growing population, but surface water reserves remain fixed and undermined by pollution, poor treatment, and limited piping infrastructure (Luo et al. 2019). Efforts to quell subsidence thus face fundamental difficulties.

These existential threats to the nation's capital have prompted two major government initiatives. Stakes are high in this context, as public funds involve forgone investment in areas like education with known aggregate benefits (Hsiao 2024b). First, a sea wall has been in discussion since 2011, with costs of up to \$40 billion (Garschagen et al. 2018, Colven 2020). Proposals for this "Great Garuda Project" have undergone several revisions, which vary in their scope and ambition. The Jakarta Coastal Defense Strategy (JCDS) in 2011 became the National Capital Integrated Coastal Development Masterplan (NCICD) in 2014, with further updates in 2016, and then the Integrated Flood Safety Plan (IFSP) in 2019. The latest in 2024 aims to protect North Java more broadly at costs of up to \$60B (Kemenko Perekonomian 2024).

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 initially 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 model coastal moral hazard in a minimal setting. The coast experiences flooding, developers construct new buildings, and the government provides flood defense. Moral hazard arises if developers do not internalize public costs and if the government is time-inconsistent.

3.1 Example

I begin with a stylized example for intuition. The government can build a sea wall to defend the coast at public cost $e > 0$. A continuum of developers can build at the coast. Developers are small, identical, and independent with mass one. If there is a sea wall, then buildings can be constructed at cost $c > 0$ and rented for revenue $r = c + \epsilon$. All developers build, and they make small private profits $\epsilon > 0$. If instead there is no sea wall, then building is not profitable because flooded buildings cannot be rented out. No developers build, and they make zero profits. Social welfare includes private profits and public costs.

The government faces a commitment problem if $r > e > \epsilon$. Before developers have built, the government prefers *ex ante* not to build the sea wall. The sea wall enables development for private profits $\epsilon < e$, which do not exceed the public cost of the sea wall. But after developers have built, the government prefers *ex post* to build the sea wall. Once the costs of development are sunk, the sea wall protects buildings that generate rental revenues $r > e$, which exceed the public cost of the sea wall.

If the government has commitment power, then it can choose the ex-ante equilibrium: no sea wall and no coastal development. Individual developers do not deviate because buildings are flooded without a sea wall, and the government does not deviate because a sea wall has no buildings to protect. This outcome is the first best, and social welfare is zero.

If the government does not have commitment power, then developers can force the ex-post equilibrium: a sea wall and full coastal development. This equilibrium is one of coastal moral hazard. Individual developers do not deviate because building behind the sea wall generates small private profits, and the government does not deviate because the sea wall is statically optimal. But the sea wall is not dynamically optimal: this outcome falls short of the first best, and social welfare is negative. Small private profits do not justify large public costs.

Reality is less stylized. First, private profits may not be small. Indeed, while sea walls are expensive, there are large returns to protecting existing megacities. If private profits justify public costs, such that $\epsilon > e$, then there is no commitment problem. However, this intuition must contend with the option to move inland. If doing so is costless over the long run, then the net gains from coastal entrenchment are limited, and so ϵ will be small.[4] Second, government intervention need not be all or nothing. The practical first best is gradual managed retreat: a sea wall today acknowledges short-run needs, while more limited intervention tomorrow enables long-run adaptation. The point is that moral hazard encourages coastal construction and slows inland migration. Expected public intervention crowds out private adaptation.

[4] Moreover, public costs must account for repeated intervention at the coast. If sea walls require continuous rebuilding, including at greater scale as sea levels rise, then the total public costs of coastal entrenchment are substantial, and so e will be large. Although if $e > r$, then there is again no commitment problem because the government does not defend in the first place.

3.2 Development and defense

I formalize and generalize the example. Consider a flood-prone coastal location. Development d and defense g generate private profits $\pi(d, g)$ at public cost $e(d, g)$. Private profits include consumer surplus for residents and producer surplus for developers. Public costs include infrastructure for flood defense and aid for flooded development. Social welfare $w(d, g)$ is private profits net of public costs.

$$w(d, g) = \pi(d, g) - e(d, g)$$

Development and defense increase private profits and public costs. For private profits, development creates buildings for residents to enjoy, and defense provides protection from coastal flooding. For public costs, development increases the need for aid, and defense incurs construction costs. That is, private profits and public costs increase monotonically in (d, g). For $d' > d$ and $g' > g$,

$$\begin{aligned} \pi(d', g) > \pi(d, g), \quad \pi(d, g') > \pi(d, g), \\ e(d', g) > e(d, g), \quad e(d, g') > e(d, g). \end{aligned}$$

Development and defense are complements. Defense raises the marginal private benefit of development by protecting new buildings from flooding. Defense also lowers the marginal public cost of development by reducing the need for post-disaster aid. That is, private profits have increasing differences in (d, g), while public costs have decreasing differences. For $d' > d$ and $g' > g$,

$$\begin{aligned} \pi(d', g') - \pi(d, g') > \pi(d', g) - \pi(d, g), \\ e(d', g') - e(d, g') < e(d', g) - e(d, g). \end{aligned}$$

The timeline has three stages: (1) the government announces a plan, (2) developers proceed with development, and (3) the government proceeds with defense. Development maximizes private profits under perfect competition, while defense maximizes social welfare. I compare outcomes to the first best, in which development and defense jointly maximize social welfare. This first best is $\hat{d}^* = d^*(\hat{g}^*)$ and $\hat{g}^* = g^*(\hat{d}^*)$

such that

$$d^*(g) = \arg\max_d \{w(d, g)\}, \quad g^*(d) = \arg\max_g \{w(d, g)\}. \tag{1}$$

3.3 Moral hazard and commitment

Moral hazard leads to coastal entrenchment: over-development and over-defense at the coast. The simple intuition is that developers do not internalize public costs, and so they tend to over-develop relative to the first best. In turn, a time-inconsistent government tends to respond with over-defense. The government can use policy to counteract this tendency, but only if it has commitment power. I study four commitment scenarios.

Strong commitment

The government can announce and commit to regulating development. If enforced, a tax $\tau = e(d, g)$ forces developers to internalize public costs.[5] As in the first best, the developer problem aligns with social welfare maximization. Equilibrium is given by $\hat{d}^C = d^C(\hat{g}^C)$ and $\hat{g}^C = g^C(\hat{d}^C)$ such that

$$d^C(g) = \arg\max_d \{w(d, g)\}, \quad g^C(d) = \arg\max_g \{w(d, g)\}. \tag{2}$$

Commitment is difficult if the tax is politically costly ex post. After development is sunk, the supply of development is perfectly inelastic. Thus, developers have strong incentives to lobby against the tax, which becomes a pure transfer from developers to the government. Moreover, the government has little benefit from the tax, which does not improve social welfare as long as development is fixed. Commitment requires resisting these static incentives not to enforce the tax.

Proposition 1. *Strong commitment achieves the first best.*

$$\hat{d}^* = \hat{d}^C, \quad \hat{g}^* = \hat{g}^C$$

Proof. Conditions 1 and 2 coincide. □

[5] Equivalently, the government can impose quantity regulation in the form of quota $\bar{d} = \hat{d}^*$, which caps development at the socially optimal level.

Weak commitment

The government can announce and commit to limited defense. If the government does not over-defend, then it forces developers not to over-develop. Development responds to defense. This indirect approach avoids the political complications of directly regulating development, but it is also less effective. Equilibrium is given by $\hat{d}^c = d^c(\hat{g}^c)$ and $\hat{g}^c$ such that

$$d^c(g) = \arg\max_d \{\pi(d,g)\}, \quad \hat{g}^c = \arg\max_g \{w(d^c(g),g)\}. \tag{3}$$

Commitment remains difficult because defense is still beneficial ex post. Suppose developers proceed with high levels of development. After development is sunk, the government can improve social welfare by providing high levels of defense. Commitment requires resisting this static incentive to deviate from the plan.

Lemma 1. *For generalized $\tilde{w}(d,g,\theta) = \pi(d,g) - (1-\theta)e(d,g)$, consider*

$$\tilde{d}(g,\theta^d) = \arg\max_d \{\tilde{w}(d,g,\theta^d)\}, \quad \tilde{g}(d,\theta^g) = \arg\max_g \{\tilde{w}(d,g,\theta^g)\}.$$

(i) $\tilde{d}(g,\theta^d)$ increases in g and θ^d, (ii) $\tilde{g}(d,\theta^g)$ increases in d and θ^g, (iii) the set of fixed points is non-empty, and (iv) the highest and lowest fixed points increase in θ^d and θ^g.

Proof. First, $\tilde{w}(d,g,\theta)$ has increasing differences in (d,g) given increasing differences for $\pi(d,g)$ and decreasing differences for $e(d,g)$. Second, $\tilde{w}(d,g,\theta)$ has increasing differences in (g,θ) because $\tilde{w}(d,g',\theta') - \tilde{w}(d,g,\theta') > \tilde{w}(d,g',\theta) - \tilde{w}(d,g,\theta)$ simplifies to $(\theta'-\theta)[e(d,g') - e(d,g)] > 0$ for $g' > g$ and $\theta' > \theta$. This condition holds because $e(d,g)$ increases in g. Third, $\tilde{w}(d,g,\theta)$ has increasing differences in (d,θ) under an analogous argument that holds because $e(d,g)$ increases in d. By Topkis's Monotonicity Theorem, these increasing differences give (i) and (ii). Tarski's Fixed Point Theorem then gives (iii), and Milgrom and Roberts (1994) Theorem 4 gives (iv). □

Proposition 2. *Weak commitment leads to coastal entrenchment.*

$$\hat{d}^c > \hat{d}^*, \quad \hat{g}^c > \hat{g}^*$$

Proof. Conditions 1 maximize the same objective, and so I can rewrite them as

$$d^*(g) = \arg\max_d \{w(d,g)\}, \quad \hat{g}^* = \arg\max_g \{w(d^*(g),g)\}.$$

By lemma 1, $\tilde{g}(d)$ increases in d for $d^c(g) > d^*(g)$, as $\tilde{d}(g,\theta^d)$ increases in θ^d for $d^c(g) = \tilde{d}(g,1)$ and $d^*(g) = \tilde{d}(g,0)$. So $\hat{g}^c > \hat{g}^*$. By lemma 1, $d^*(g) = \tilde{d}(g,0)$ increases in g. Thus, $\hat{d}^c = d^c(\hat{g}^c) > d^*(\hat{g}^c) > d^*(\hat{g}^*) = \hat{d}^*$ given $d^c(g) > d^*(g)$. So $\hat{d}^c > \hat{d}^*$. □

Weak non-commitment

Developers can ignore the government's announcement and proceed to over-develop. If the government cannot commit, then its announcement is not credible. Equilibrium is given by $\hat{d}^n = d^n(\hat{g}^n)$ and $\hat{g}^n = g^n(\hat{d}^n)$ such that

$$d^n(g) = \arg\max_d \{\pi(d,g)\}, \quad g^n(d) = \arg\max_g \{w(d,g)\}. \tag{4}$$

Indeed, after development is sunk, the government finds it difficult to enforce regulation or to limit defense. Defense responds to development. Static incentives prevail.

Proposition 3. *Weak non-commitment worsens coastal entrenchment.*

$$\hat{d}^n > \hat{d}^c, \quad \hat{g}^n > \hat{g}^c$$

Proof. Consider $(\hat{d}^*, \hat{g}^*)$, where $w(\hat{d}^*, \hat{g}^*) > w(\hat{d}^n, \hat{g}^n)$ by definition. By lemma 1, $\hat{d}^* < \hat{d}^n$ and $\hat{g}^* < \hat{g}^n$ because these equilibria increase in θ^d, where $(\hat{d}^*, \hat{g}^*)$ corresponds to $(\theta^d, \theta^g) = (0,0)$ and $(\hat{d}^n, \hat{g}^n)$ corresponds to $(\theta^d, \theta^g) = (1,0)$. That is, decreasing d and g relative to $(\hat{d}^n, \hat{g}^n)$ improves social welfare. With weak commitment, the government can move in this direction by decreasing g relative to $\hat{g}^n$. By lemma 1, developers respond by decreasing d relative to $\hat{d}^n$ because $d^c(g) = d^n(g) = \tilde{d}(g,1)$ increases in g. So $\hat{g}^c < \hat{g}^n$. Thus, $\hat{d}^c = d^c(\hat{g}^c) < d^n(\hat{g}^n) = \hat{d}^n$. So $\hat{d}^c < \hat{d}^n$. □

Strong non-commitment

The government can itself encourage over-development. Suppose a current government pursues private profit maximization for political gain, adopting lax regulation that spurs development while not internalizing public costs. A future government is left to provide defense and pay the costs. If the current government over-develops, then it forces the future government to over-defend, as defense responds to development. Equilibrium is given by $\hat{d}^N$ and $\hat{g}^N = g^N(\hat{d}^N)$ such that

$$\hat{d}^N = \arg\max_d \big\{\pi(d, g^N(d))\big\}, \quad g^N(d) = \arg\max_g \big\{w(d,g)\big\}. \tag{5}$$

Indeed, the future government cannot regulate the current government, which has since left office. Furthermore, the future government finds it statically optimal to provide defense after development is sunk. This tension between current and future governments relates to concerns of “odious debt” (Jayachandran and Kremer 2006). I can similarly frame tensions between local and national governments or between national governments and international aid. Developer associations may also coordinate to wield their aggregate influence over defense.[6]

Proposition 4. *Strong non-commitment greatly worsens coastal entrenchment.*

$$\hat{d}^N > \hat{d}^n, \quad \hat{g}^N > \hat{g}^n$$

Proof. In contrast to social welfare maximization in the first best, private profit maximization gives $\hat{d}^\pi = d^\pi(\hat{g}^\pi)$ and $\hat{g}^\pi = g^\pi(\hat{d}^\pi)$ such that

$$d^\pi(g) = \arg\max_d \big\{\pi(d,g)\big\}, \quad g^\pi(d) = \arg\max_g \big\{\pi(d,g)\big\}.$$

By definition, $\pi(\hat{d}^\pi, \hat{g}^\pi) > \pi(\hat{d}^n, \hat{g}^n)$. By lemma 1, $\hat{d}^\pi > \hat{d}^n$ and $\hat{g}^\pi > \hat{g}^n$ because these equilibria increase in θ^g, where $(\hat{d}^\pi, \hat{g}^\pi)$ corresponds to $(\theta^d, \theta^g) = (1,1)$ and $(\hat{d}^n, \hat{g}^n)$ corresponds to $(\theta^d, \theta^g) = (1,0)$. That is, increasing d and g relative to $(\hat{d}^n, \hat{g}^n)$ improves private profits. With strong non-commitment, the current government can move in this direction by increasing d relative to $\hat{d}^n$. By lemma 1, the future government responds by increasing g relative to $\hat{g}^n$ because $g^N(d) = g^n(d) = \tilde{g}(d,0)$ increases in d. So $\hat{d}^N > \hat{d}^n$. Thus, $\hat{g}^N = g^N(\hat{d}^N) > g^n(\hat{d}^n) = \hat{g}^n$. So $\hat{g}^N > \hat{g}^n$. $\square$

[6] If there is no such coordination, either by the government or by developer associations, then moral hazard is restricted to the weak non-commitment case. Small developers do not internalize their individual influence over defense.

3.4 Discussion

Moral hazard generates coastal lock-in at high public cost. Global mean sea level rise projections reach as high as 1m in 2100 and 2m in 2150 under SSP5-8.5 (Fox-Kemper et al. 2021), and local land subsidence will lead to even worse scenarios for many large coastal cities, particularly in Asia (Tay et al. 2022). Gradual inland retreat, as Desmet et al. (2021) envision, calls for declining coastal development given growing long-run risk. But reality is one of coastal persistence and even intensification (Kocornik-Mina et al. 2020, Lin et al. 2024). Moral hazard leads to coastal entrenchment that attracts coastal residents, slows inland migration, and lowers the incentives for inland development.[7] The consequence is continued spending on coastal defense and large damages should it fail.

I note comparisons to moral hazard in the insurance setting. First, the typical challenge is hidden action. The principal cannot control risk-taking by the agent because this risk-taking is unobserved. Here, the challenge is time inconsistency. The government defends the coast not because development is hidden, but rather because it is ex-post optimal to do so after development is sunk. Second, the typical distortion is uninternalized risk, such that protection leads to excessive risk-taking. Here, the distortion is amplified. Risk-taking itself prompts further protection, thereby creating a feedback loop. Defense encourages development, which forces added defense.

I also clarify the conditions for moral hazard. The monotone comparative statics analysis shows that these conditions do not include continuity or differentiability. Sea wall construction can be a discrete choice, as in the example. However, moral hazard is eliminated at several extremes. First, there is no moral hazard if defense is entirely infeasible. But international aid may bolster capacity to defend, and indeed plans for Jakarta draw in part on Dutch expertise. Second, there is no moral hazard if defense is costless. But sea walls are large-scale undertakings, which must reach far above sea level to minimize overtopping risk during storm surges. Third, there is no moral hazard if there is no private adaptation to crowd out. Coastal defense is necessary when there is no scope for inland retreat. Disaster relief is necessary when vulnerable

[7] The baseline model has a single coastal location, such that coastal entrenchment comes at the implicit expense of other locations. Appendix B shows that coastal defense crowds out inland development by making this spatial interaction explicit. Appendix B also shows that public defense crowds out private defense more broadly.

populations lack other means to adapt.

Finally, I discuss alternative solutions beyond strong commitment. First, coastal taxes or quotas can minimize moral hazard. Both still require commitment to enforcement, which can be undercut by lobbying. Second, local governments might rely on local financing, such that defense today must eventually be recovered through higher taxes. But cost-sharing is common in practice. National ministries have led sea wall planning for Jakarta and contributed funding for initial construction.[8] Third, mandated insurance is difficult because coastal flooding is an aggregate risk. Zurich does not want to pool with Jakarta, which floods every year. If insurance is fairly priced, then the premium amounts to a large tax that invites lobbying. If insurance is subsidized, then the subsidy gives rise to moral hazard. Fourth, Coasian bargaining may allow inland stakeholders to pay to avoid coastal entrenchment. But inland interests are diffuse relative to coastal interests, and the transfers involved may be too large to be politically feasible. Given these challenges, the empirical analysis focuses instead on assessing variations of partial commitment.

4 Empirics

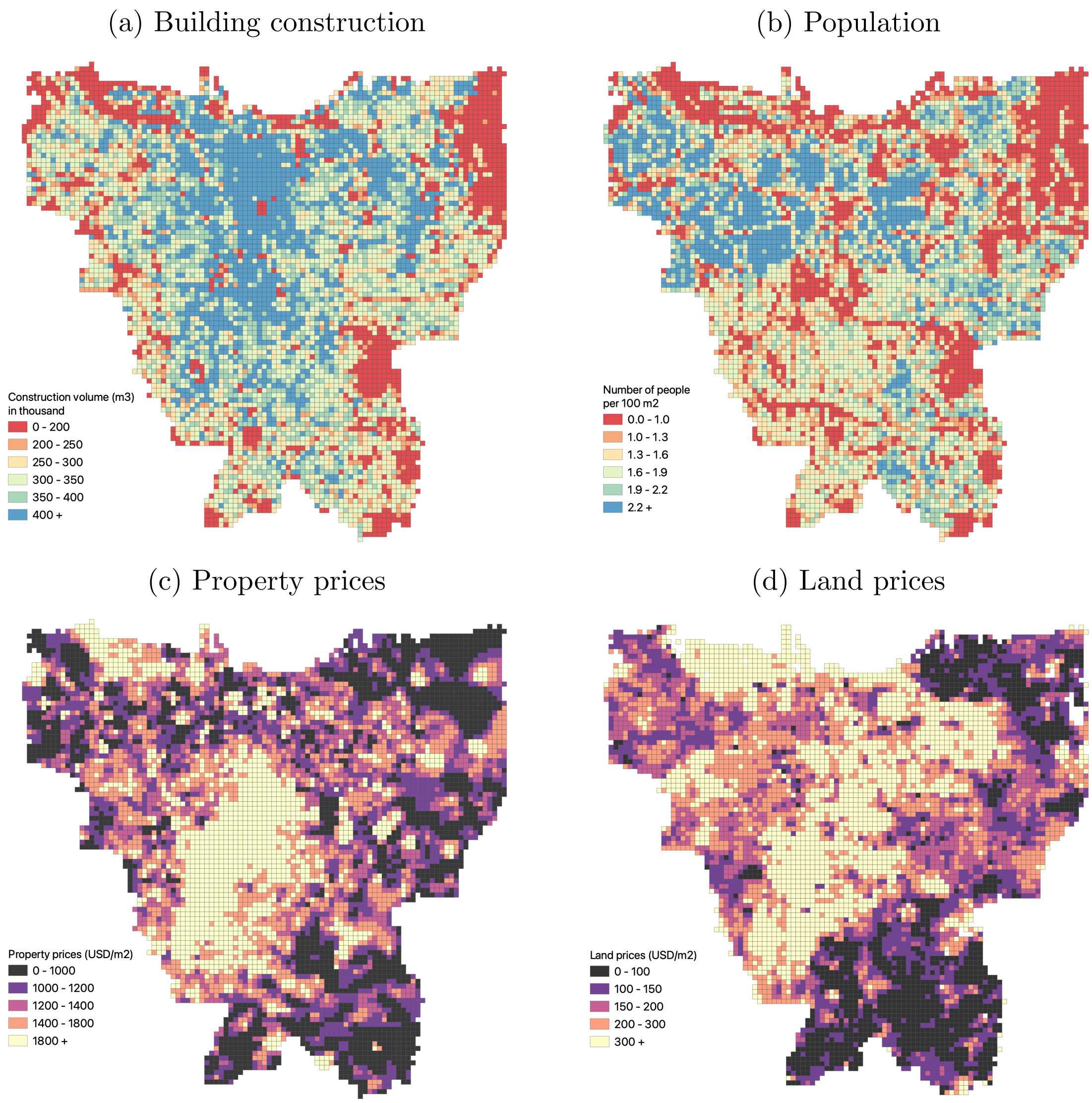
The theory frames the empirics. I compile data on development, defense, and flooding, and I show how development responded to historical flood defense.

4.1 Data

I compile high-resolution spatial data on building construction, populations, property prices, land prices, and flooding across Jakarta. The city is divided into five districts (*kota*), 44 sub-districts (*kecamatan*), 267 neighborhoods (*kelurahan*), and 2,722 tracts (*rukun warga*), with each tract containing around 4,000 people. I compile data by 300m cell, or roughly three times finer than tract level. I focus on Jakarta proper, but the empirical analysis will allow for movement across the broader metropolitan area. I exclude the islands of *Kepulauan Seribu* district. Figure 2 illus-

[8] In Jakarta, the national ministries of public works (*PUPR*) and development planning (*Bappenas*) have been directly involved in sea wall planning. Proposed funding in the first phase is 64% federal and 36% local (Kemenko Perekonomian 2024). Beyond Jakarta, New York City sea wall plans propose funding that is 65% federal, 35% state, and 0% municipal (USACE 2022). Even with local financing, inland residents help to fund coastal defense despite not benefiting directly.

Figure 2: Data (2015)



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

trates the data, and appendix C provides additional detail.

The Global Human Settlement Layer measures building construction and populations across Jakarta (GHSL 2022). It does so by 100m cell every five years from 1975 to 2020, and I aggregate to the 300m cell level. The construction data record built-up surface areas and volumes, separating residential from non-residential construction. I verify the 2015 measures by comparing them to 2015 data from Visicom, a provider of satellite-derived 3D maps that capture building heights at the 1m pixel level. When aggregated by tract, the correlation between the datasets exceeds 0.90. The population data are downscaled from regional administrative data based on the distribution and density of residential buildings, as measured in the construction data. This approach assumes that residents occupy development, consistent with my empirical model in which rents clear markets for development in equilibrium.

I construct property prices for 2015 with data on transactions and listings from two major real estate websites, 99.co and brickz.id, covering both residential and non-residential properties. From 99.co, I scrape and successfully geocode 56,222 listings with prices and floor spaces for October 2022. I compute average property prices by 300m cell. From brickz.id, I obtain 6,929 property transactions for 2015. I use these data to backcast the 2022 prices and to adjust for differences between listed and transacted prices. I thus obtain transacted property prices for 2015, where property prices combine building and land values.

Land prices for 2015 come from the Jakarta Smart City initiative, through which the city government and the National Land Agency (*Badan Pertanahan Nasional*) sought to update property tax appraisals and improve collections. They did so by computing land prices at a granular level, drawing on administrative data from transactions, market data from brokers and online platforms, and property characteristics from field visits.[9] The data include 20,892 observations at the sub-block level, with land prices measured as prices per square meter. I aggregate to the 300m cell level. Harari and Wong (2024) describe these data in further detail and take additional steps to verify their quality, including in informal areas. Moreover, the use of these values for tax collection gives them official weight.

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

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

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

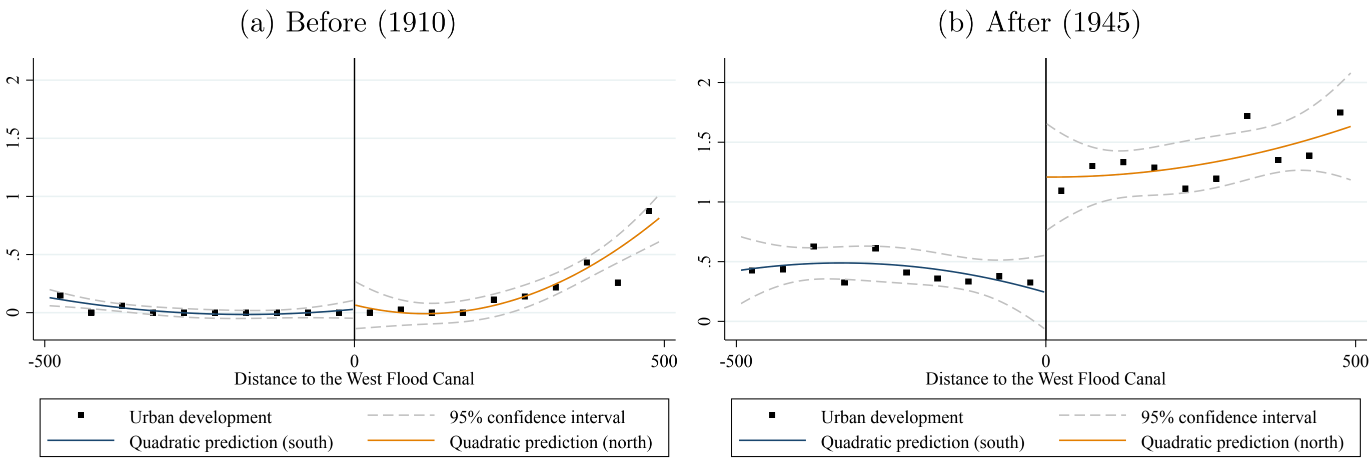
4.2 Historical flood defense

I consider whether historical investments in flood protection led to higher levels of land development. The opening of the West Flood Canal in 1918 allows me to study this dynamic over the last century, with historical maps from the Dutch colonial era providing measures of land development both before and after the construction of the canal. I georeference eight maps that cover the period from 1887 to 1945 in six- to eight-year intervals. I digitize them to construct a panel that records, over time, whether each 50m cell contains developed or undeveloped land. I then aggregate to the 100m cell by counting the developed 50m cells within each 100m cell. This aggregation allows me to accommodate misalignment over time, which otherwise introduces conflicting measures of development from year to year.

The West Flood Canal diverts floodwaters that flow from the higher-elevation south to the lower-elevation north, protecting neighborhoods north of the canal but not those south of the canal. In the spirit of Almond et al. (2009), I leverage this spatial discontinuity to study how land development responds to flood protection.[10] I restrict attention to cells in the vicinity of the canal, and I plot land development relative to distance to the canal. I find that defense encourages development. In figure 3, land development jumps at the boundary after the opening of the canal, but not before, as development responds positively to increased flood protection. Appendix C shows regression estimates by year, and it documents decreased flooding north of the boundary, smoothness in elevation across the boundary, and smoothness in land development across the boundary throughout the pre-canal period.

[10] Almond et al. (2009) compare air quality in Chinese cities to the north and south of the Huai River in China. Northern cities receive free coal for winter heating, while southern cities do not.

Figure 3: Land development and the West Flood Canal



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

5 Demand

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

5.1 Model

Residents are renters that make static location choices over space. Individuals i choose locations k to maximize residential utility, which is given by representative utility v_k and logit shocks ϵ_{ik}.

$$U = \max_k \{v_k + \epsilon_{ik}\} \quad \text{for} \quad v_k = \alpha r_k + \phi f_k + x_k \gamma + \varepsilon_k \tag{6}$$

Representative utility depends on rents r_k, flooding f_k, observed amenities x_k, and unobserved amenities ε_k. Residents seek low rents, low flooding, and high amenities. Defense decreases flooding, increasing demand and in turn encouraging development. The endogeneity problem is that residents demand unobserved amenities, and they bid up rents accordingly. Rents will be correlated with unobserved amenities.

Logit shocks give a closed-form expression for residential choice probabilities ρ_k.

The denominator captures spatial interdependence: flooding in one location affects demand for every location.

$$\rho_k = \frac{\exp(v_k)}{\sum_\ell \exp(v_\ell)} \tag{7}$$

In the rental market, demand for each location is

$$D_k^{\text{res}} = N\varphi\rho_k$$

for total population N and average floor space φ per resident. I take each as given in the data. The inside options are locations in the core of Jakarta. The outside option is, collectively, all locations in the periphery. The total population combines core and periphery, and it evolves exogenously. By the typical log-sum formula, welfare is

$$\Pi^{\text{res}} = \frac{1}{\alpha} \ln \sum_k \exp(v_k).$$

The model captures how flooding affects residential welfare and location choices. The latter determines how flooding affects rents in equilibrium. The key parameters are flooding coefficient ϕ, which measures the disutility of flooding, and rent coefficient α, which allows me to monetize this disutility. Moral hazard increases in monetized disutility $\frac{\phi}{\alpha}$. Intuitively, strong distaste for flooding implies large rent increases from flood protection, such that development has large gains from forcing defense.

5.2 Estimation

I estimate demand by matching the spatial distribution of the population in 2015. I take rents to be mortgage payments on observed property prices.[11] I take flooding to be as observed from 2013 to 2020. I focus on mean flooding because Jakarta floods consistently, although the variance of flooding may create uncertainty that also affects utility. I assume the periphery is free of flooding, and I set peripheral rents to the minimum observed within the core. For $\Delta X_k = X_k - X_0$ and reference location $k = 0$, inverting equation 7 gives an estimating equation.

$$\Delta \ln \rho_k = \alpha \Delta r_k + \phi \Delta f_k + \Delta x_k \gamma + \Delta \varepsilon_k \tag{8}$$

[11] I compute rents $r_k = \tau p_k^1$ from observed prices p_k^1, where I set $\tau = 8.4\%$ to reflect annual payments on a 30-year mortgage at Bank Indonesia's 2015 benchmark interest rate of 7.5%.

Table 1: Residential demand estimates

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

Each observation is a 300m cell. IV estimation matches population shares, and the first stage is a regression with rents as the dependent variable. Rents are yearly mortgage payments, which I compute from property prices in 2015. Flooding is as observed from 2013 to 2020. Residential amenities measure proximity to schools, health clinics, and passenger rail stations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Estimation is by linear regression. I address rent endogeneity and mismeasurement by instrumenting with ruggedness as a cost shifter.

5.3 Estimates

Table 1 presents demand estimates, defining locations as 300m cells. I find that demand is decreasing in rents and in flooding. The flooding coefficient captures the welfare benefits of decreasing flooding with a sea wall, and the rent coefficient monetizes these benefits. Demand is increasing in residential amenities, as measured by proximity to schools, health clinics, and passenger rail stations. As an instrument, ruggedness raises rents with a large F-statistic in the first stage.

I consider magnitudes by comparing coefficients. The rent and flooding coefficients suggest that mean flood levels require a \$2.30 decrease in yearly rents per square meter as compensating variation. Annual construction of 7M square meters of floor space from 1999 to 2013 (BPS 2022), combined with a 5% depreciation rate, suggests 140M square meters of total floor space. Multiplying this total by \$2.30 implies yearly damages of \$320M, consistent with \$300M in accounting damages estimated by Budiyono et al. (2015). Flooding has a standard deviation of 0.26 meters per year. Increasing flooding by one and two standard deviations implies further yearly damages of \$560M and \$1.1B. Increasing flooding by four standard deviations corresponds to one-meter inundation, which remains within range of sea level rise projections by 2100 (Fox-Kemper et al. 2021). Yearly damages rise to \$2.2B.

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

Another concern is that flooding may be correlated with unobserved amenities. But I estimate a flooding coefficient that implies reasonable valuations of yearly flood damages, as computed above. On one hand, flood zones may enjoy positive amenities. If coastal proximity bundles flooding and ocean views, then it attenuates the impact of flooding on demand. This bias understates the moral hazard problem. But controlling for coastal distance reveals a small, positive effect on demand, such that coastal amenities seem not to weigh heavily. On the other hand, flood zones may suffer negative amenities. If flooding impedes public and private investment, then it worsens conditions beyond its direct consequences. But such effects are part of flood damages. An alternative is to study discontinuities in official flood risk measures (Bakkensen and Ma 2020), but doing so requires disentangling risk perceptions from preferences.

I instead isolate preferences by considering how residents respond to actual flooding, which residents observe contemporaneously. I thus infer the welfare impacts of future flooding from residents' reactions to historical flooding. Implicitly, I take historical flooding, which is largely pluvial and fluvial, as informative of future flooding, which is largely coastal. While flooding is flooding, some extrapolation is unavoidable as sea level rise comes with flooding at unprecedented levels. And while historical flooding does capture tail risk, including 30- and 50-year floods in 2013 and 2020, it does not capture permanent future inundation. In understating the damages from inundation, I understate moral hazard.

I do not directly capture dynamics, costly migration, or endogenous amenities. First, I model residents as myopic and thus constrain dynamics to the supply side. The resulting bias is ambiguous and depends on the nature of expectations.[12] Second, I allow residents to move frictionlessly across space and thus understate the costs of moving inland. This assumption simplifies estimation and is arguably appropriate for the long-run counterfactuals of interest, as migration costs are minimal over long time horizons. Appendix D shows how to model and estimate migration costs. Third, I recover amenities and hold them fixed in counterfactuals, even as flooding takes hold and residents move inland. That is, I do not allow inland agglomeration to improve inland amenities, and so I overstate the costs of moving inland. Consequently, I understate the cost of coastal lock-in and moral hazard.[13]

6 Supply

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

6.1 Model

Landowners make forward-looking investments in durable, immobile development, which they lease for rental revenue. Development and defense are complements because defense offers flood protection that raises rents. In each location k and period t, landowners i have individual plots of developed or empty land. Individual state $d_{ikt} \in \{1, 0\}$ records whether plots are developed or empty, and h_{ikt} records building heights of developed plots. The choices are whether to develop and how high to build. These choices are permanent, and both contribute to densification. They depend on aggregate state s_t, which tracks rents r_{kt}, construction costs c_{kt}, property prices p^1_{kt}

[12] On one hand, suppose flood realizations affect beliefs. Current flooding increases expected future flooding, and forward-looking residents react strongly to this permanent shock. A static model attributes the strong response to current flooding alone, thereby overstating the disutility of flooding. On the other hand, suppose expectations are correct and unaffected by realizations. Current flooding does not increase expected future flooding, and forward-looking residents react modestly to this transient shock. A static model attributes the modest response to current flooding alone, thereby understating the disutility of flooding.

[13] At the same time, inland improvements are themselves costly, and these costs attenuate the bias from holding amenities fixed. Separately, I do not account for the cosmetic disamenities of a sea wall, as I do not observe large-scale sea walls in the data.

for developed plots, and land prices p^0_{kt} for empty plots across locations k.

$$s_t = \{r_{kt}, c_{kt}, p^1_{kt}, p^0_{kt}\}_k$$

Landowners are small and take the aggregate state as given. Landowners draw individual cost shocks but are otherwise homogeneous within locations: they face equal rents, costs, and prices. However, the model accommodates rich heterogeneity across locations, and the data allow me to define locations granularly.

Landowners of developed plots collect rents, then choose to sell or hold. Denoting developed state $d_{ikt} = 1$ with superscripts one, the value function is

$$V^1_{kt}(h) = \alpha r_{kt} h + \tilde{V}^1_{kt}(h), \tag{9a}$$

$$\tilde{V}^1_{kt}(h) = \max\{\alpha p^1_{kt} h,\ \beta \mathbb{E}[V^1_{kt+1}(h)]\} \tag{9b}$$

for building height h. I write $V^1_{kt}(h) = V^1_k(h, s_t)$ and $\tilde{V}^1_{kt}(h) = \tilde{V}^1_k(h, s_t)$, such that subscripts t denote dependence on state s_t. In the first line, landowners collect rents r_{kt} for each floor of building height. Parameter α is the utility of money, and it governs how strongly development responds to increased rents. Landowners then receive the value $\tilde{V}^1_{kt}(h)$ of a choice. In the second line, this choice is to sell or hold. If they sell, they collect property price p^1_{kt} for each floor of building height. If they hold, they receive the value $V^1_{kt+1}(h)$ of continuing to own a developed plot in the next period. Expectations are over future state s_{t+1}.

Landowners of empty plots choose to develop, sell, or hold. Denoting empty state $d_{ikt} = 0$ with superscripts zero, the value function is

$$V^0_{kt} = \mathbb{E}[\max\{\hat{V}^1_{kt} + \varepsilon^1_{ikt},\ \tilde{V}^0_{kt} + \varepsilon^0_{ikt}\}], \tag{10a}$$

$$\hat{V}^1_{kt} = \max_h\{\beta^{b+1}\mathbb{E}[V^1_{kt+b+1}(h)] - c_{kt}(h)\}, \tag{10b}$$

$$\tilde{V}^0_{kt} = \max\{\alpha p^0_{kt},\ \beta\mathbb{E}[V^0_{kt+1}]\}. \tag{10c}$$

In the first line, landowners choose to develop or not given idiosyncratic logit shocks $(\varepsilon^1_{ikt}, \varepsilon^0_{ikt})$. Expectations are over the logit shocks. In the second line, landowners have chosen to develop. They then choose building height h to maximize expected profits. Building high increases rentable floorspace and thus the expected value $V^1_{kt+b+1}(h)$

of owning development, subject to time to build b. But building high also increases construction costs $c_{kt}(h)$. Expectations are over future state s_{t+b+1}. In the third line, landowners have chosen not to develop. They then choose to sell or hold. If they sell, they collect land price p^0_{kt}. If they hold, they receive the value V^0_{kt+1} of continuing to own an empty plot in the next period. Expectations are over future state s_{t+1}.

Construction costs are a function of building height h, flooding f_{kt}, observed costs x_{kt}, and unobserved costs ε_{kt}. For $\theta = (\alpha, \phi, \gamma, \varepsilon)$, I note the distinction between supply parameters θ^{dev} in this section and demand parameters θ^{res} in the last section, although I suppress these superscripts to lighten notation.

$$c_{kt}(h) = \frac{1}{2}\omega h^2 + \phi f_{kt} + x_{kt}\gamma + \varepsilon_{kt} \tag{11}$$

Common costs within locations will imply common choices h_{kt} of building height. These costs are upfront costs: future owners must bear future flow costs, and so flow costs are captured by property prices. Building height faces convexity ω. Flooding can be costly if flood protection involves private investment, while observed costs capture other dimensions of spatial heterogeneity. The endogeneity problem is that property prices depend on construction, which depends on unobserved costs. Property prices will be correlated with unobserved costs.

Logit shocks give development choice probabilities δ_{kt}. Development is increasing in the value $\hat{V}^1_{kt}$ of owning a developed plot and decreasing in the value $\tilde{V}^0_{kt}$ of owning an empty plot.

$$\delta_{kt} = \frac{\exp\big(\hat{V}^1_{kt}\big)}{\exp\big(\hat{V}^1_{kt}\big) + \exp\big(\tilde{V}^0_{kt}\big)} \tag{12}$$

In the rental market, supply in each location is

$$D^{\text{dev}}_{kt+b+1} = \sum_i [d_{ikt} + (1 - d_{ikt})\delta_{kt}]h_{kt}.$$

By the typical log-sum formula, welfare is

$$\Pi^1_{kt}(h) = r_{kt}h + \frac{1}{\alpha}\tilde{V}^1_{kt}(h), \quad \Pi^0_{kt} = \frac{1}{\alpha}\ln\Bigg(\exp\big(\hat{V}^1_{kt}\big) + \exp\big(\tilde{V}^0_{kt}\big)\Bigg).$$

The model captures how flooding affects landowner welfare and development choices. The latter determines how flooding affects rents in equilibrium. The key parameters are rent coefficient α and construction costs c_{kt}. Moral hazard increases in α. If rents are valuable, then development has large gains from raising rents by forcing defense. Moral hazard also increases in c_{kt}. If construction costs are high, then development generates low profits that depend crucially on defense. Development thus has large gains for forcing defense. Stated differently, large construction costs are large sunk costs that amplify the difference between ex-ante and ex-post incentives to defend. This difference drives time inconsistency and thus moral hazard.

6.2 Equilibrium

Flooding affects rents, property prices, and land prices in equilibrium. In the rental market, equilibrium rents equalize residential demand and developer supply.

$$D_{kt}^{\text{res}}(r_{kt}) = D_{kt}^{\text{dev}}(r_{kt}) \quad \forall\, k, t$$

Flooding reduces rents by reducing residential demand. In the property and land markets, risk-neutral real estate investment trusts (REITs) have competitive demand for both developed and empty plots. Equilibrium prices are therefore given by landowner indifference between selling or not in each period.

$$\tilde{V}_{kt}^{1}(h) = \alpha p_{kt}^{1} h = \beta \mathbb{E}[V_{kt+1}^{1}(h)], \quad \tilde{V}_{kt}^{0} = \alpha p_{kt}^{0} = \beta \mathbb{E}[V_{kt+1}^{0}] \tag{13}$$

If rents are high relative to property prices, then REITs arbitrage by purchasing developed plots and collecting rents over time. If rents are high relative to land prices, then REITs arbitrage by purchasing empty plots, developing them, and collecting rents. Perfect competition leads to complete arbitrage. I thus obtain pricing equations

$$p_{kt}^{1} = \sum_{t'=1}^{\infty} \beta^{t'} \mathbb{E}[r_{kt+t'}], \quad p_{kt}^{0} = \frac{\beta}{\alpha} \ln \left(\exp\big(\mathbb{E}[\hat{V}_{kt+1}^{1}]\big) + \exp\big(\mathbb{E}[\tilde{V}_{kt+1}^{0}]\big) \right).$$

Prices are tied to rents. Property prices p_{kt}^{1} are the net present value of collecting rents over time. Land prices p_{kt}^{0} are the option value of development, which in turn depends on rents. Flooding reduces prices by reducing rents.

6.3 Estimation

I estimate supply by matching the spatial distribution of new construction between 2015 and 2020. Dynamics introduce the challenge of computing continuation values. Inverting equation 12,

$$\ln \delta_{kt} - \ln(1-\delta_{kt}) = \hat{V}^1_{kt} - \tilde{V}^0_{kt}.$$

Development choices depend on $\hat{V}^1_{kt}$ and $\tilde{V}^0_{kt}$, which by definitions 10b and 10c contain continuation values $V^1_{kt+b+1}(h)$ and V^0_{kt+1}. These continuation values typically require specifying expectations and solving the model. I instead read these values from the data in the spirit of Kalouptsidi (2014). In particular, by equations 13, observed prices capture continuation values. First, $\tilde{V}^0_{kt} = \alpha p^0_{kt}$ holds directly. Second, applied to definition 10b,

$$\hat{V}^1_{kt} = \max_h \{\alpha \beta^b \mathbb{E}[p^1_{kt+b}]h - c_{kt}(h)\}.$$

Third, taking the first order condition and applying cost equation 11,

$$h_{kt} = \frac{\alpha \beta^b}{\omega} \mathbb{E}[p^1_{kt+b}].$$

Tall construction h_{kt} reflects high expected property prices p^1_{kt+b}.[14] Finally, combining the above, I obtain an estimating equation.

$$\ln \delta_{kt} - \ln(1-\delta_{kt}) = \frac{1}{2}\omega h^2_{kt} - \alpha p^0_{kt} - \phi f_{kt} - x_{kt}\gamma - \varepsilon_{kt} \tag{14}$$

Estimation reduces to simple linear IV regression. The main data requirements are measures of building construction and land prices. Indeed, such measures are available in many urban settings, although perhaps not in rural settings. Building construction data give probabilities $\hat{\delta}_{kt}$ of new development, which I compute from the data in a first stage. I do so by applying a frequency estimator and smoothing nonparametrically across bins. Building height data give h_{kt}. Prices act as numeraire, and I assume $\beta = 0.95$. The endogeneity problem can be seen directly: unobserved

[14] I measure h_{kt}, and so I do not need to specify time to build b. Without measures of h_{kt}, the alternative is to impose specific values for h and b, then work directly with expected property prices $\mathbb{E}[p^1_{kt+b}]$. Doing so requires additional structure on expectations. By rational expectations, for example, $\mathbb{E}[p^1_{kt+b}] = p^1_{kt+b} + \eta_{kt}$ for observed p^1_{kt+b} and expectational error η_{kt}.

Table 2: Developer supply estimates

	IV		First stage (h^2_{kt})		First stage (P^0_{kt})		
	Estimate	SE	Estimate	SE	Estimate	SE	Mean
Building height (m)	1.415***	(0.412)					9.29
Land prices (100 USD/m^2)	0.169***	(0.039)					11.8
Residential amenities (km)			1.381***	(0.372)	0.191***	(0.045)	2.91
Flooding (m/year)	0.063	(0.042)	-6.226**	(3.043)	-0.917***	(0.246)	0.15
Ruggedness (index)	-0.148***	(0.055)	9.879**	(4.924)	1.462***	(0.123)	1.43
District FE	x		x		x		
Observations	5,780		5,780		5,780		
F-statistic			13.75		17.80		

Each observation is a 300m cell. IV estimation matches development probabilities, and I show first stage regressions with building heights and land prices as dependent variables. Land prices are from 2015. Flooding is as observed from 2013 to 2020. Residential amenities measure proximity to schools, health clinics, and passenger rail stations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

costs ε_{kt} affect the supply of development, which influences rents over time and thus both property prices p^1_{kt} and land prices p^0_{kt}. Land prices appear directly as a regressor, while property prices appear indirectly through building heights h_{kt}. I address price endogeneity and mismeasurement by instrumenting with residential amenities as demand shifters.

6.4 Estimates

Table 2 presents supply estimates, defining locations as 300m cells. I find that supply is increasing in prices. The price coefficient captures how strongly developers respond to higher prices when sea wall construction reduces flooding and raises demand. Supply is unresponsive to flooding beyond this demand-side effect on prices, and flooding may even encourage development conditional on prices. The mean level of flooding decreases costs by a small and statistically insignificant \$6 per square meter, perhaps reflecting government intervention. Supply is decreasing in ruggedness, which at mean levels imposes costs of \$125 per square meter. As an instrument, residential amenities raise prices with large F-statistics in the first stage.

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

Equations 13 are key for estimation. They imply that observed prices reflect expected future profits, thereby sidestepping the need to compute continuation values. First, I assume that efficient markets equalize prices and expectations. 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, which load onto unobserved costs, but counterfactuals will hold them fixed.[15]

Second, I abstract from developer market power. If development is not perfectly competitive, then observed prices do not fully capture continuation values. That is, individual developers affect market prices, and so their development choices change market prices relative to those that I observe in the data. I maintain this simplification because my focus is on strategic interaction between development and defense, rather than among individual developers. For estimation, the assumption is that developers take prices as given. I fully allow for moral hazard under weak non-commitment, by which individual developers act taking aggregate development as given.[16] I also allow for moral hazard under strong non-commitment through a current government, local government, or developer association that encourages aggregate development, including through weak coastal regulation, even as individual developers act competitively.

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

[16] This aggregate-individual interplay echoes "big K, little k" distinctions in macroeconomics.

I do not allow for moral hazard through individual developers that are large enough to influence either market prices or aggregate development, but developers are small indeed. Government data for Jakarta record 14,505 construction companies in 2021, including 1,024 with annual revenues exceeding \$3.5M (BPS 2022). Competitive pressure exists even at the top end.

The main advantage of my approach is that estimation remains flexible on expectations, including as they relate to future flooding and defense. In effect, equations 13 recast the long-run decision to develop and rent as a short-run decision to develop and sell outright. I accommodate long-run expectations of any form because they capitalize into prices that I observe. Expected flooding and defense affect rents, but forward-looking markets capitalize these expectations into prices. The same applies for moral hazard. If the current government encourages coastal development with weak regulation, knowing that the future government must bear the cost of defense, then this encouragement boosts coastal prices. That is, estimation with price data accommodates a range of complex, long-run expectations without the need to specify them explicitly. Prices act as a sufficient statistic for the incentives to develop.

Finally, I compare approaches for dynamic discrete choice estimation. The full-solution approach is computationally intensive, with repeated calculation of continuation values following the nested fixed point algorithm of Rust (1987). Two-step approaches simplify computation by estimating continuation values from data, applying conditional choice probability methods from Hotz and Miller (1993).[17] The Euler conditional choice probability approach of Scott (2013) perturbs the timing of investment to derive a linear estimating equation, offering straightforward estimation, transparent identification, and flexibility on expectations.[18]

I retain these benefits, but I note several differences. Appendix D treats development as a terminal action to derive an Euler estimating equation, as in Hsiao (2024a).

[17] Ackerberg et al. (2007), Aguirregabiria and Mira (2010), and Arcidiacono and Ellickson (2011) review this literature.

[18] The Euler approach exploits finite dependence, which holds when two sequences of actions with different initial choices lead to the same distribution of future states. Finite dependence allows continuation values to difference out. Arcidiacono and Miller (2011) show how two-step approaches can apply finite dependence more generally to relax assumptions on expectations and the evolution of state variables beyond the sample period, including in non-stationary models.

For $\Delta X_{kt} = X_{kt} - \beta X_{kt+1}$ and expectational error η_{kt},

$$\Delta \ln \delta_{kt} - \ln(1-\delta_{kt}) = \frac{1}{2}\omega \Delta h_{kt}^2 - \phi \Delta f_{kt} - \Delta x_{kt}\gamma - \Delta \varepsilon_{kt} + \eta_{kt}.$$

First, the Euler approach accounts for dynamics by leaning heavily on the exact timing of observed choices, comparing action in periods t and $t+1$. I lean instead on observed variation in prices across space. Second, the Euler approach applies rational expectations, such that $\mathbb{E}[X_{kt+1}] = X_{kt+1} + \eta_{kt}$. I assume instead that the future is capitalized into current prices. Third, the Euler approach requires two periods of data to construct differences ΔX_{kt}. I only require one period.

7 Government

I characterize the benefits of government intervention with a hydrological flood model, and I capture the costs with engineering estimates.

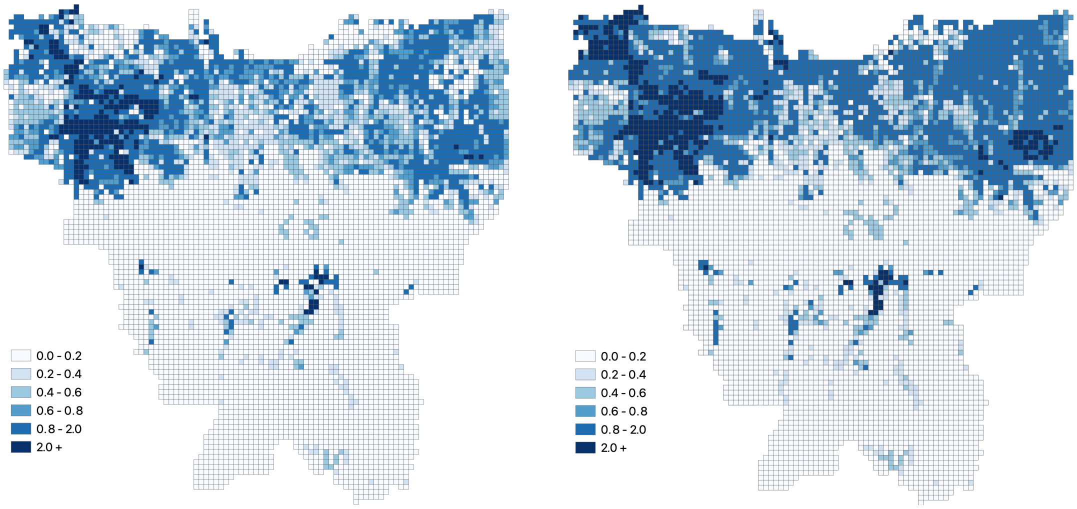
7.1 Benefits

A hydrological model of flooding captures the benefits of a sea wall, which reduces flooding across Jakarta. I adopt a machine-learning approach to modeling flooding, following the frontier in hydrology as reviewed by Mosavi et al. (2018). I train and validate the model on observed flooding from 2013 to 2020, which I measure monthly and at the tract level. As input data, I use rainfall, elevation, slope, and distances to major rivers, minor rivers, and the coast. I train a range of machine learning models and find that a histogram gradient boosting decision tree performs best. I impose monotonicity constraints on distance to major rivers and elevation, which help to reduce overfitting by applying basic physical properties without the complexity of modeling the full physical system. Appendix D describes this procedure in detail.

The trained model characterizes how a sea wall affects flooding across Jakarta. Figure 4 shows the impact of a sea wall, which I simulate by raising the elevation of the city. The predictions align with intuition. The coastal north benefits most from the sea wall, particularly in low-elevation areas that flood regularly in the absence of defense. A small set of coastal areas benefit only modestly because flood risk is very high, such that flooding persists even with defense. At the same time, some parts

Figure 4: Reductions in flooding

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



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

of the high-elevation south also benefit from a sea wall, as improved drainage in the north alleviates river flooding in the south.[19] I ignore existing sea wall protections, which a 2020 government report calls "very poor" (NCICD 2020). I do not consider partial, neighborhood-specific sea wall construction because only a full sea wall, which extends across the entirety of Jakarta Bay, can hold back the sea.

Similarly, I simulate future sea level rise and land subsidence by lowering the elevation of the city. For global mean sea level rise, I use central projections from the IPCC: 0.20m by 2050, 0.56m by 2100, and 0.92m by 2150 (Fox-Kemper et al. 2021). Each is relative to sea levels in 2014, which I treat as a 2015 baseline. I assume that sea levels rise at constant rates within 50-year intervals, and I extrapolate linearly beyond 2150 based on average annual rates from 2014 to 2150. For local land subsidence, I use projections from Andreas et al. (2018) for 2050. These projections are specific to Jakarta, heterogeneous across space, and relative to land elevation in 1977. Subsidence exceeds 5m in some northern neighborhoods. I compute changes relative to 2017 estimates, which I treat as a 2015 baseline. I again assume constant

[19] A benefit of the machine learning approach is that it can capture this interaction without the need to specify the complex physical processes that determine river drainage.

rates within 50-year intervals, and I extrapolate linearly beyond 2050 based on average annual rates from 1977 to 2050.

7.2 Costs

I focus on direct costs of Jakarta's planned sea wall. I obtain engineering cost estimates from government reports on the planned wall, which runs onshore along the coast and offshore through Jakarta Bay (NCICD 2014, 2020). Onshore length is 60km with a height of 4m, while offshore length is 32km with a height of 24m, of which 8m is above water. Estimated costs are \$11B in 2014 USD: construction costs of \$2B onshore and \$6B offshore, plus maintenance costs that add 35% in net-present-value terms.[20] Government plans seek protection against sea levels of up to 4m above street level, as land subsidence drives expectations of 3m to 5m by 2050.

I use these estimates to project costs for sea walls of alternative heights. I assume that 1m of sea level rise requires walls with 1m of height onshore and 2m of above-water height offshore, following the ratios of the current plan. For example, relative to the planned 4m sea wall, the 3m wall of figure 4 would require 3m of height onshore and 6m offshore. I compute costs following Lenk et al. (2017), who analyze cost estimates for sea walls in Canada and the Netherlands. They find costs to be roughly linear in height and length. Indeed, I find this linearity to hold for Jakarta, where both onshore and offshore estimates imply similar unit costs despite different heights and lengths. For a sea wall of height g in meters, costs reflect onshore and offshore unit costs of \$10.67M and \$10.78M per meter-kilometer, heights of g and $2g + 16$ meters, and lengths of 60 and 32 kilometers. For 3m and 5m sea walls, total costs are thus \$9.5B and \$12B.[21]

In focusing on these direct costs, I understate the moral hazard problem. The greater the uninternalized costs of defense, the greater the incentives to engage in coastal moral hazard. First, I abstract from the opportunity costs of public funds,

[20] The 2014 and 2020 plans provide similar estimates once adjusted for differences in proposed offshore sea wall lengths (25km in 2014 vs. 32km in 2020). Total costs for 2014 include pumping stations, jetties, and mangrove restoration, and those for 2020 include pumping stations, retention basins, and river dikes. I exclude non-flood investments in transport, land reclamation, and port development, which in early plans brought the total to \$40B.

[21] For a 3m wall, offshore above-water and total heights are 6m and 22m. For a 5m wall, these heights are 10m and 26m. Each is relative to 8m and 24m for the planned 4m wall. I can also consider cost uncertainty, which Lenk et al. (2017) find is well captured by a factor of three.

which are likely to be substantial. The billions spent on the sea wall could instead be spent on education and health infrastructure inland. Second, I abstract from the costs of disaster aid, which are not as well documented in official records. The consequence is that the empirical analysis of moral hazard will be restricted to the strong commitment and strong non-commitment cases of the theoretical analysis.[22]

8 Counterfactuals

I quantify the moral hazard problem by showing how coastal development and defense vary with government commitment. Integrated policy alleviates moral hazard.

8.1 Solving the model

I focus on the strong commitment and strong non-commitment cases of the theoretical analysis in section 3, and I refer simply to commitment and non-commitment. I extend the single-location, single-period model across multiple locations and periods. Under commitment, I solve the analogues of equilibrium conditions 2 for development and defense (d^C, g^C). Under non-commitment, I solve the analogues of equilibrium conditions 5 for (d^N, g^N). I solve across locations in spatial equilibrium and across periods with backward induction over a finite horizon from 2050 to 2500, as detailed in appendix E.1. I treat the 2015 data as initial conditions.

For tractability, I simplify the spatial dimension by aggregating over 300m cells and solving across 267 neighborhoods. I simplify the time dimension by imposing that government investment in defense occurs at 50-year intervals, reflecting that sea walls last up to 50 years before requiring major repair. Defense maintains full efficacy during its lifespan, then depreciates fully. I allow residents to move and developers to build every five years, but I constrain development to proceed at a constant pace within each 50-year interval.

[22] The focus on sea wall costs implies $e(d, g) = e(g)$, which incorporates uninternalized costs of defense but not of development. In this case, strong commitment, weak commitment, and weak non-commitment coincide because commitment to g fixes $e(g)$, and so it is equivalent for development d to maximize private profits $\pi(d, g)$ or social welfare $w(d, g) = \pi(d, g) - e(g)$. An alternative to disaster aid is internalities, which reintroduce uninternalized costs of development. This approach would take engineering costs of flood damages as a paternalistic benchmark for private flood damages, then draw a contrast to those internalized by residents, as revealed in demand estimation by where residents choose to live.

8.2 Quantifying moral hazard

I quantify moral hazard by studying commitment of varying degrees. This commitment dictates the government's ability to resist static incentives in favor of dynamically optimal strategies. Full commitment achieves the first best by holding to a pre-announced, fixed path of defense that maximizes social welfare over time. In every period, defense does not respond to development, and the government internalizes both current and future costs of defense. This formulation is equivalent to full regulation that taxes development for the costs of defense. By contrast, no commitment allows for moral hazard. In every period, defense responds to development, and so development takes advantage to force added defense at uninternalized cost.

Partial commitment lies between these extremes, and it acknowledges rotating governence. Limited commitment is phased out. The government acts with full commitment in 2050 to maximize social welfare over time, weighing both current and future costs of defense. But then future governments act with no commitment. Conversely, delayed commitment is phased in. The government acts with no commitment in 2050. Then future governments act with full commitment to maximize social welfare over time. In both cases, political myopia undercuts commitment by creating moral hazard across administrations. If current governments do not internalize future costs of defense, which are borne instead by future governments, then current governments themselves engage in over-development and defense at the coast.

Table 3 presents the results. I report new coastal development and defense over time relative to their full-commitment outcomes. I define the coast as the administrative region of North Jakarta, which covers 22% of Jakarta's land area and includes the entirety of the coast. I report city-wide social welfare impacts in dollar terms relative to a scenario with zero defense. As is typical of logit models, welfare impacts are identified in changes but not levels. Appendices E.2 and E.3 plot coastal development and defense from 2050 to 2250, including under zero defense.

Full commitment leads to gradual coastal retreat. Coastal defense protects development in the short term, when private gains outweigh public costs. Defense rises over time as sea level rise takes hold, but defense rises at a restricted pace. Coastal development then falls as coastal risk grows in severity. By contrast, no commitment leads to stronger and more sustained coastal defense, which encourages coastal devel-

Table 3: Commitment

	Coastal development			Coastal defense			Social welfare
	2050	2100	2200	2050	2100	2200	NPV
Full commitment	1.00	0.67	0.30	1.00	1.36	1.77	14.73
No commitment	1.62	1.30	0.84	1.34	2.05	3.07	-4.66
Limited commitment	0.86	1.45	0.94	0.92	1.71	2.86	1.01
Delayed commitment	1.50	0.50	0.22	1.27	1.55	1.85	12.30
Limited myopic commitment	1.32	1.36	0.88	1.17	1.92	2.99	-1.06
Delayed myopic commitment	1.58	1.06	0.53	1.32	1.89	2.56	6.26

Coastal development and defense are new development and defense activity in North Jakarta in 2050, 2100, and 2200. I normalize each by dividing by full-commitment outcomes in 2050. Social welfare is a net present value measured in 1B USD with 2015 dollars, relative to the zero-defense scenario. Each row is one counterfactual. Full commitment chooses defense upfront and adheres to the plan. No commitment chooses defense in a sequential static manner. Limited commitment is full commitment in 2050, then no commitment. Delayed commitment is no commitment in 2050, then full commitment. Under political myopia, governments that act with commitment internalize their own costs of defense but not future costs of defense, which fall instead on future governments.

opment and delays coastal retreat – even despite substantial sea level rise. In 2200, new coastal development activity is nearly three times as high under no commitment as it is under full commitment.

I also consider welfare impacts. Under full commitment, government action generates \$14.73B in social welfare gains relative to inaction. While these gains are meaningful, they are modest in comparison to total GDP of more than \$200B in 2024 alone (BPS 2025). Without coastal defense, coastal flooding prompts residents to move inland, bidding up inland rents and increasing inland development. Consistent with Desmet et al. (2021), inland gains offset coastal losses and mitigate overall damages. But it is precisely because of this inland alternative that coastal moral hazard is socially costly. Under no commitment, government action leads to welfare losses of \$4.66B relative to inaction. Social welfare is lower than in the zero-defense scenario because over-defense at the coast is costly. Moral hazard eliminates the first-best welfare gains, and it is severe enough that even inaction dominates. The difference between full and no commitment – nearly \$20B – captures the resulting welfare losses.

Appendices E.4 and E.5 consider robustness and extensions. For robustness, I perturb the assumed discount factor, the estimated demand and supply elasticities, and the imposed horizon and timing. As extensions, I consider political lobbying for development, uncertainty over future flood risk, amenities that improve with inland migration, and depreciation of coastal development. The qualitative results hold throughout.

8.3 Partial commitment

Partial commitment can help. Limited commitment dominates no commitment, achieving welfare gains of $1.01B relative to inaction. I note that commitment in 2050 involves low levels of coastal development and defense, even relative to the first best. The reason is that the current government has first-mover advantage, and so it can influence the extent to which future development forces future defense. The current government uses this advantage to protect future governments from moral hazard, incurring short-run losses in order to realize long-run gains. Even so, delayed commitment is more impactful because it involves a longer period of commitment. This commitment limits the extent to which development in 2050 can force future defense, even as delayed commitment allows development to force defense in 2050. The resulting welfare gains of $12.30B, relative to those under full commitment in every period, suggest that non-commitment in 2050 comes at a social cost of $2.43B.

Political myopia undercuts both limited and delayed commitment. Under limited commitment, the current government only protects future governments if it internalizes the future costs of defense. Otherwise, political myopia encourages the current government to do just the opposite: engaging in moral hazard and forcing future defense. Future defense raises future rents and thus current real estate prices, which the current government values. Future defense also reduces the current need to move inland, which the current government finds costly. As such, the current government uses its first-mover advantage to push coastal concerns onto future administrations. Coastal activity is elevated relative to the first best, leading to welfare losses of $1.06B, and inaction dominates again. At the same time, coastal activity and social welfare losses are still reduced relative to no commitment. Current development cannot force current defense, as the current government uses its commitment power to avoid being exploited itself. Finally, political myopia undercuts delayed commitment to an even greater extent, but it still allows for welfare gains of $6.26B.

Table 4: Integrated policy

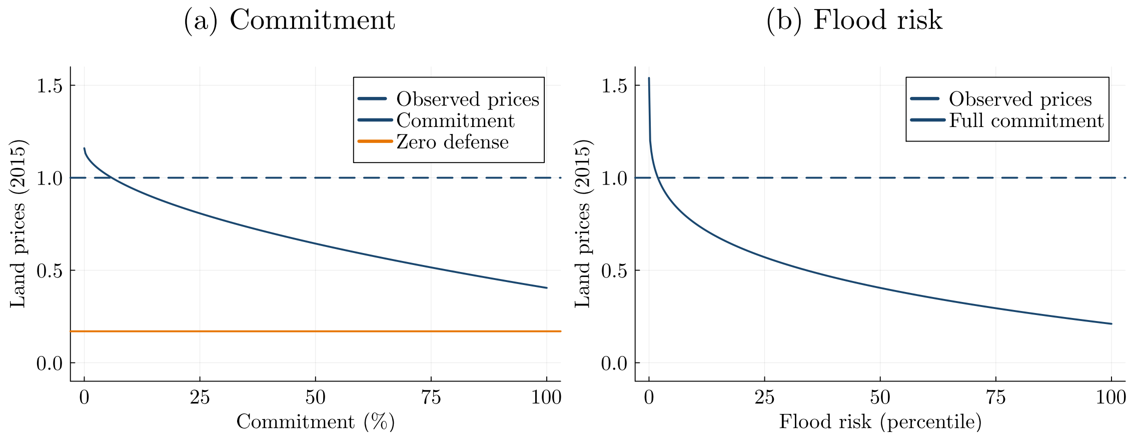
	Coastal development			Coastal defense			Social welfare
	2050	2100	2200	2050	2100	2200	NPV
Inland investment							
Full commitment	0.77	0.53	0.26	0.68	0.90	1.16	13.77
No commitment	1.07	0.83	0.50	0.80	1.15	1.63	10.04
Subsidence control							
Full commitment	0.81	0.50	0.19	0.67	0.88	1.09	22.33
No commitment	1.03	0.69	0.31	0.76	1.04	1.36	20.46
Coastal regulation							
Full commitment	0.79	0.58	0.32	0.89	1.20	1.61	11.15
No commitment	1.22	1.04	0.75	1.12	1.68	2.57	-0.95

Coastal development and defense are new development and defense activity in North Jakarta in 2050, 2100, and 2200. I normalize each by dividing by full-commitment outcomes in 2050. Social welfare is a net present value measured in 1B USD with 2015 dollars, relative to the baseline zero-defense scenario. Each row is one counterfactual. Full commitment chooses defense upfront and adheres to the plan. No commitment chooses defense in a sequential static manner. Integrated policy combines coastal defense with inland investment that reduces coastal demand by 25%, subsidence control that slows land subsidence by 25%, or coastal regulation that imposes 25% of the Pigouvian tax.

8.4 Integrated policy

Table 4 shows how integrated policy navigates the commitment problem. I pair sea wall defense with three complementary policies. First, I consider inland investment that reduces coastal demand by 25%. Lower gains from forcing defense lessen moral hazard substantially. Government action dominates inaction even under no commitment. Second, I slow land subsidence by 25%. Lower flood risk increases welfare, and smaller gains from defense lessen moral hazard. Government action again dominates inaction. Eliminating subsidence requires expensive technology and strong regulation, but I show that modest reductions are still effective. Third, I impose regulation equivalent to 25% of the Pigouvian tax on coastal development. As with subsidence, perfect regulation is challenging. But even imperfect regulation undercuts moral hazard. Moral hazard remains strong enough that zero defense dominates defense with no commitment, but the difference is smaller than it is without coastal regulation.

Figure 5: Coastal prices



The left figure computes model-implied coastal land prices in 2015 while varying government commitment. Sea level rise is the central, baseline projection. I take commitment to be fixed over time, and I define a simple measure $g(x) = xg^C + (1-x)g^N$ of partial commitment for $x \in [0,1]$, full-commitment g^C, and non-commitment g^N. The right figure computes model-implied prices while varying flood risk. The government acts with full commitment. I normalize observed prices to one.

8.5 Coastal prices

I argue that moral hazard has at least partially driven development to date. I do so through the lens of the model by computing model-implied prices, which I compare to the prices I observe in the data. Figure 5 plots the comparison for coastal land prices in 2015. In the left subfigure, I vary the level of government commitment while fixing sea level rise to be as projected in baseline. Model-implied prices under zero defense are much lower than observed, indicating the market's faith in government capacity to defend. Less commitment leads to more coastal defense and higher coastal rents over time, implying higher coastal prices. Thus, high observed prices suggest that current development anticipates low levels of government commitment. That is, inverting the model allows me to infer expectations from data. I note that this inversion relies crucially on the flexibility of estimation with respect to these expectations. If I needed to specify expected non-commitment when estimating model parameter from data, then the data and estimated model would be tautologically consistent with expected non-commitment.

I also ask whether biased flood perceptions can explain high coastal prices. In the right subfigure, I vary the extent of sea level rise and thus the path of future flood risk. The baseline sea level rise scenario draws on central projections from Fox-Kemper et al. (2021), and it corresponds to the 50th percentile of flood risk. I draw on the full range of projections to construct a range of flood risk scenarios. Throughout, I shut off moral hazard by imposing full commitment. I find that appealing to flood perceptions alone requires extreme and prolonged optimism to match observed prices. Moral hazard can rationalize observed prices, but flood perceptions cannot.[23]

8.6 Policy implications

Dynamic effects call for commitment to long-run adaptation policy, but commitment is difficult in practice. I offer two policy recommendations for navigating this challenge. First, partial commitment remains helpful. Persistence allows current policy to have future benefits, even if implemented temporarily. Limited commitment helps to reduce moral hazard, particularly when forward-looking governments internalize the costs of future defense. Similarly, anticipation allows future policy to have current benefits. Delayed commitment and opposition-party pledges can each generate welfare improvements today.

Second, integrated policy further alleviates moral hazard. This policy accepts the political difficulty of commitment at the coast and instead proceeds more indirectly. In particular, it pairs sea wall construction with inland investment policies aimed at reducing coastal demand. Indeed, current efforts to relocate the political capital from Jakarta are consistent with such an approach. I show that these efforts, even if externally motivated, also lessen coastal frictions. Integrated policy can also seek to slow land subsidence and strengthen coastal regulation. Despite the challenges in doing so, any incremental progress serves to reduce coastal moral hazard. These moral hazard benefits should be considered alongside the direct benefits of such policies.

9 Conclusion

This paper studies adaptation to sea level rise in Jakarta, the second-most populous city in the world. Jakarta provides an early view into the future for other major

[23] Each exercise fixes discount factor $\beta = 0.95$. With larger β, future flooding implies low future rents that cannot rationalize high asset prices today. With smaller β, the low net present value of rents again cannot rationalize high asset prices today.

coastal cities like Bangkok, Shanghai, and New York, which are under threat as sea levels continue to rise worldwide (Hsiao 2025). I show that adaptation faces important frictions, including over the long run, as government intervention can worsen lock-in by creating moral hazard at the coast. I quantify the welfare losses from moral hazard, and I evaluate policy options for navigating this challenge. Government commitment reduces moral hazard but is subject to fundamental political constraints, although partial commitment remains helpful. Integrated policy acknowledges these constraints and allows for welfare gains even absent full commitment.

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APPENDIX

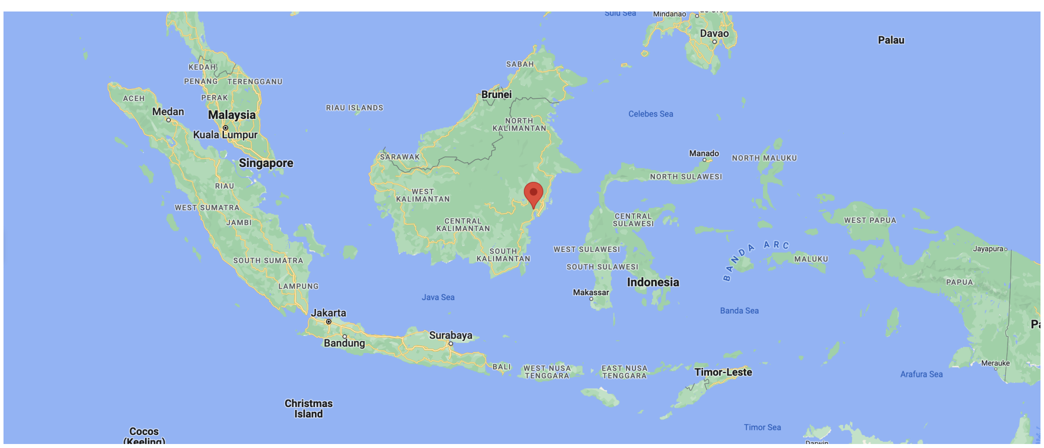
A Background

Moving the capital

Figure A1: Nusantara

(a) Plans

(b) Location



Source: Ministry of Public Works and Public Housing (*Kementerian PUPR* via ikn.go.id) and Google Maps. The top figure shows a government visualization of the planned city. The bottom figure shows its location in what is currently East Kalimantan province.

B Theory

Coastal and inland locations

Consider two locations: coastal and inland. I study coastal development d, coastal defense g, and inland development δ. There is no inland flooding and thus no inland defense. Social welfare is private profits net of public costs.

$$w(d, g, \delta) = \pi(d, g, \delta) - e(d, g)$$

As in the baseline model, private profits have increasing differences in (d, g), while public costs have decreasing differences. Residents choose across space, such that inland and coastal locations are substitutes. Thus, inland development lowers the marginal benefit of coastal development and defense by drawing residents away from the coast. That is, private profits have decreasing differences in (d, δ) and (g, δ). For $d' > d$, $g' > g$, and $\delta' > \delta$,

$$\pi(d', g, \delta') - \pi(d, g, \delta') < \pi(d', g, \delta) - \pi(d, g, \delta),$$
$$\pi(d, g', \delta') - \pi(d, g, \delta') < \pi(d, g', \delta) - \pi(d, g, \delta).$$

Social welfare maximization gives the first best. For comparison, I focus on a spatial equilibrium under weak non-commitment by the government. Development maximizes private profits, and defense maximizes social welfare. The first best is $\hat{d}^* = d^*(\hat{g}^*, \hat{\delta}^*)$, $\hat{g}^* = g^*(\hat{d}^*, \hat{\delta}^*)$, and $\hat{\delta}^* = \delta^*(\hat{d}^*, \hat{g}^*)$, and the spatial equilibrium is $\hat{d}^S = d^S(\hat{g}^S, \hat{\delta}^S)$, $\hat{g}^S = g^S(\hat{d}^S, \hat{\delta}^S)$, and $\hat{\delta}^S = \delta^S(\hat{d}^S, \hat{g}^S)$ such that

$$\begin{aligned}
d^*(g, \delta) &= \arg\max_d \{w(d, g, \delta)\}, & d^S(\delta, g) &= \arg\max_d \{\pi(d, g, \delta)\},\\
g^*(d, \delta) &= \arg\max_g \{w(d, g, \delta)\}, & g^S(d, \delta) &= \arg\max_g \{w(d, g, \delta)\},\\
\delta^*(d, g) &= \arg\max_\delta \{w(d, g, \delta)\}, & \delta^S(d, g) &= \arg\max_\delta \{\pi(d, g, \delta)\}.
\end{aligned}$$

Proposition 5. *Coastal development and defense crowd out inland development.*

$$\hat{d}^S > \hat{d}^*, \quad \hat{g}^S > \hat{g}^*, \quad \hat{\delta}^S < \hat{\delta}^*$$

Proof. I note that $d(g, -\delta)$ increases in g and $-\delta$ because $\pi(d, g, \delta)$ has increasing differences in (d, g) and decreasing differences in (d, δ). Similarly, $g(d, -\delta)$ increases in d and $-\delta$, and $-\delta(d, g)$ increases in d and g. As in lemma 1, for generalized $\tilde{w}(d, g, \delta, \theta) = \pi(d, g, \delta) - (1 - \theta)e(d, g)$, these increasing differences imply that the highest and lowest fixed points $(d, g, -\delta)$ are increasing in θ. I thus obtain the result. □

Public and private defense

Consider two means of coastal defense: public and private. I study development d, public defense g, and private defense γ. Social welfare is private profits net of public costs.

$$w(d,g,\gamma) = \pi(d,g,\gamma) - e(d,g,\gamma)$$

For simplicity, fix development d. Public and private defense are substitutes. Private profits have decreasing differences in (g,γ) because public defense g lowers the marginal returns to private defense γ. Public costs have increasing differences in (g,γ) because public defense g reduces the need for post-disaster aid and thus lowers the public cost savings from private defense γ. For $g' > g$ and $\gamma' > \gamma$,

$$\begin{aligned} \pi(d,g',\gamma') - \pi(d,g',\gamma) < \pi(d,g,\gamma') - \pi(d,g,\gamma), \\ e(d,g',\gamma') - e(d,g',\gamma) > e(d,g,\gamma') - e(d,g,\gamma). \end{aligned}$$

The first best is $\hat{g}^*(d) = g^*(d,\hat{\gamma}^*)$ and $\hat{\gamma}^*(d) = \gamma^*(d,\hat{g}^*)$, and the defensive equilibrium under weak non-commitment is $\hat{g}^G(d) = g^G(d,\hat{\gamma}^G)$ and $\hat{\gamma}^G(d) = \gamma^G(d,\hat{g}^G)$ such that

$$\begin{aligned} g^*(d,\gamma) &= \arg\max_g \big\{w(d,g,\gamma)\big\}, \qquad & g^G(d,\gamma) &= \arg\max_g \big\{w(d,g,\gamma)\big\}, \\ \gamma^*(d,g) &= \arg\max_\delta \big\{w(d,g,\gamma)\big\}, \qquad & \gamma^G(d,g) &= \arg\max_\delta \big\{\pi(d,g,\gamma)\big\}. \end{aligned}$$

Proposition 6. *Public defense crowds out private defense.*

$$\hat{g}^G > \hat{g}^*, \quad \hat{\gamma}^G < \hat{\gamma}^*$$

Proof. I note that $g(-\gamma)$ increases in $-\gamma$ because $w(d,g,-\gamma)$ has increasing differences in $(g,-\gamma)$. Similarly, $\gamma(-g)$ increases in $-g$ because $\pi(d,g,-\gamma)$ has increasing differences in $(g,-\gamma)$. As in lemma 1, for generalized $\tilde{w}(d,g,\gamma,\theta) = \pi(d,g,\gamma) - (1-\theta)e(d,g,\gamma)$, these increasing differences imply that the highest and lowest fixed points $(g,-\gamma)$ are increasing in θ. I thus obtain the result. □

There is ambiguous impact on development d, which is given by $d(g,\gamma) = \arg\max_d\{\pi(d,g,\gamma)\}$. Private profits have increasing differences in (d,g) and (d,γ), as public and private defense are substitutes. More public defense $\hat{g}^G > \hat{g}^*$ encourages more development, while less private defense $\hat{\gamma}^G < \hat{\gamma}^*$ encourages less development.

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.

Figure A1: Co-determination of development and defense

(a) Development given defense

(b) Defense given development

Source: PIK2 Sedayu Indo City (via sedayuindocitypik2.com) 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.

At the same time, the government cites private development in planning for and marketing proposed investments in coastal defense.

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.

C Data

Table C1 lists data sources. This section details data construction and validation.

Building construction

These data come from the Global Human Settlement Layer, with measurements at the 100m pixel level. Jakarta consists of 65,260 such pixels. For building construction, 1,900 pixels feature an increase in measured built-up volume between 2015 and 2020. I verify these data with 2015 data from Visicom, a company that produces satellite-derived 3D maps that capture building heights at the 1m pixel level. These maps rely on light detection and ranging (lidar) data, which satellites collect by emitting pulsed laser beams and measuring reflection times. Beams that reflect quickly imply taller building heights, with measurements accurate to the meter. When aggregated to the tract level, the correlation between Global Human Settlement Layer and Visicom measures is 0.90 for built-up surface and 0.92 for built-up volume. Figure C1 shows the comparison visually.

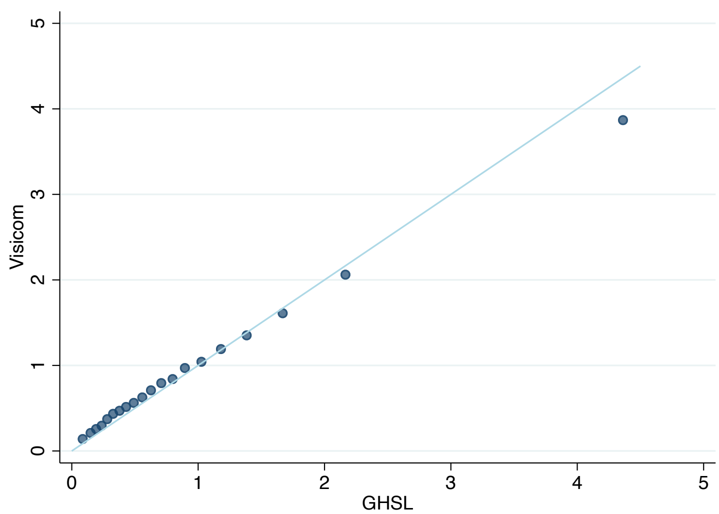
Property prices

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

Table C1: Data sources

Period	Source (description)
1975-2020	Global Human Settlement Layer (building construction, populations)
2015	Visicom (building construction)
2022	99.co (property prices)
2015	Brickz.id (property prices) (Harari and Wong 2024)
2015	Jakarta Smart City (land prices)
2013-2020	Regional Disaster Management Agency (flooding)
2022	Jakarta Satu (schools, clinics, rail stations, roads)
1887-1945	Dutch colonial maps (historical land development)

Figure C1: Building volumes (1M m^3), GHSL vs. Visicom



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

Table C2: 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.

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 C2 shows the high rate of success in geocoding.

Third, I construct property prices at the 300m cell level. I compute prices per square meter by dividing prices by floor space, dropping the 1% of listings without information on prices or building areas. I collapse listings with identical addresses – primarily apartment listings within complexes – into single observations by taking means. I then aggregate to the tract level as follows. For the 70% of tracts with more than five observations, I take the mean. For the 30% of tracts with less than five observations, I compute an inverse-distance-weighted mean of nearby observations.[24] I thus obtain property prices for 2022.

Fourth, I backcast the 2022 prices to 2015. I obtain data on 2015 property transactions from Brickz (*www.brickz.id*), as scraped and kindly shared by Harari and Wong (2024). The 2015 data contain 6,929 observations that I use to compute 2015-2022 adjustment factors by district. I do so by computing district means in 2015 and 2022, reweighing 2022 prices to match the property type composition of the 2015 data. The resulting adjustment factors capture price changes over time, as well as differences between transacted and listed prices. I then apply the adjustment factors to the 2022 data to obtain 2015 prices. Relying directly on the 2015 prices would be more straightforward, but the relatively small number of geocoded observations – around half of the 6,929 transactions – complicates measurement at the tract level.

Historical land development

I construct a panel of historical land development by digitizing maps of Batavia from the Dutch colonial era. These maps come from the digital collections of Leiden University Libraries. Table C3 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.

[24] 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 C3: 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).

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 C2. I select these points to prioritize accuracy in the vicinity of the National Monument and the West Flood Canal, with a modified set of points before the canal is constructed. I implement the overlay with first-order polynomial (affine) transformation and nearest-neighbor resampling. This affine transformation preserves the collinearity of points by applying only rotation, scaling, and translation, avoiding image distortions but ruling out the exact matching of more than two control points.

I digitize maps with unsupervised machine learning. In each map, red shading denotes built-up areas, while green and write denote undeveloped lands. I divide maps into 50m cells, then I take the modal R, G, and B values across pixels in each cell to obtain one RGB code per cell. I apply a k-means clustering algorithm on these RGB codes to group cells with similar colors. I choose k to obtain no more than one grouping of red cells, and I code these cells as built-up. This approach reduces noise in the image files, which contain red in many different shades. The 1910 map marks built-up areas with red dots instead of shading, and so I apply shading manually then digitize it as above. Figure C3 overlays the image inputs and the digitization outputs, which together illustrate the accuracy of this procedure.

I then ask whether the construction of the West Flood Canal in 1918 led to increased land development in protected areas. I leverage a spatial discontinuity in flooding at the boundary of the canal, which protects areas to its north but not to its south. I plot the discontinuity in land development around the boundary in the main text, alongside the lack of a discontinuity before the canal's opening. In this analysis and what follows, I aggregate the historical land development data to the 100m cell level by counting the number of developed 50m cells within each 100m cell. Misalignment across maps can cause measurements at the 50m cell level to

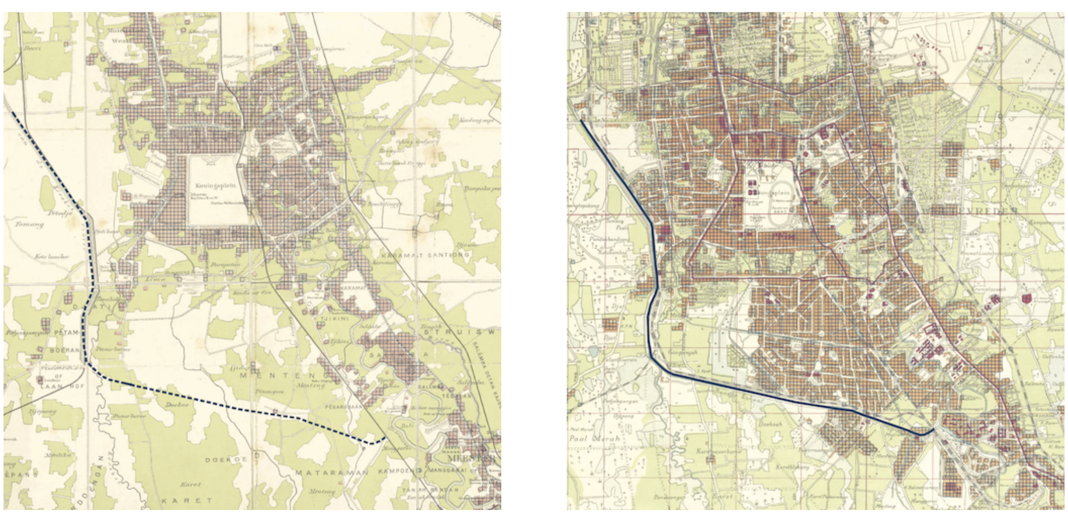
Figure C2: Ground control points for georeferencing

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

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

Figure C3: Land development and the West Flood Canal

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



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

Table C4: Land development at the canal boundary by year

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

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

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 C4 draws on data from the full panel to measure the discontinuity in each available year. For cell c and year t, the specification is

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

for land development Y_{ct}, dummy N_c for being on the protected north of the canal, and year fixed effect δ_t. I compute an optimal bandwidth of 500m, and I restrict attention to cells within this distance from the boundary. I also show robustness to this choice. The coefficients of interest are the β terms by year. Cell and year 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 C4 provides further validation checks, showing that elevation is smooth across the boundary and that the canal indeed offers flood protection to its north.

A similar pattern holds in the modern cross-section. Lower flood risk is associated with higher land prices and more building construction in 2015. Table C5 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.

Other potential concerns remain. 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, particularly at the level of 100m cells. Second, flooding may not be the only driver of post-canal land development. For example, the north is closer to the fast-growing city center. But I restrict attention around the boundary, which minimizes differences in proximity, and I show the absence of pre-canal differences in growth. The canal itself imposes a physical barrier between north and south, but 15 crossings minimize this barrier over the 10km stretch of canal that I study. Finally, the canal may facilitate other forms of government intervention by establishing clear boundaries for favored neighborhoods. Such effects remain consistent with the theory, which only requires that government intervention increase residential value.

D Estimation

Residential choice with costly migration

For an individual i in origin j considering destination k, utility is

$$u_{ijk} = \underbrace{\alpha r_k + \phi f_k + x_k \gamma + \varepsilon_k}_{\mu_k} + \tau m_{jk} + \epsilon_{ijk}$$

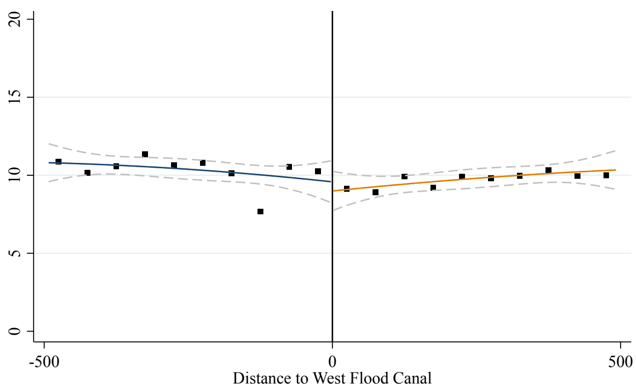
for migration distance m_{jk}. Logit shocks give choice probabilities

$$\rho_{jk} = \frac{\exp(\mu_k - \tau m_{jk})}{\sum_{\ell} \exp(\mu_\ell - \tau m_{j\ell})}.$$

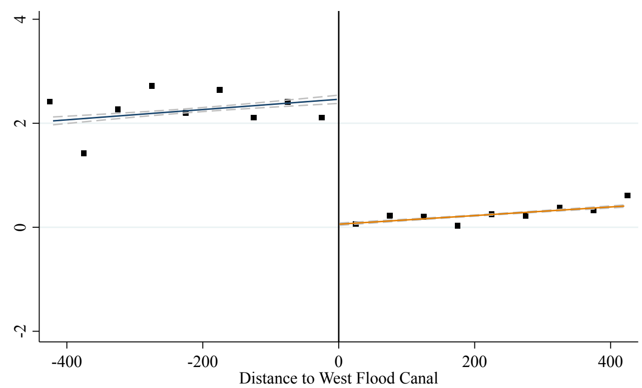
If residents are not perfectly mobile, such that $\tau > 0$, then estimation follows Berry (1994) and Berry et al. (1995). The only difference is that I integrate over origins,

Figure C4: Validating the spatial regression discontinuity design

(a) Elevation



(b) Flood frequency (2013-2020)



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

Table C5: Flooding, land prices, and building construction

(a) Land price ($\$/m^2$)

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

(b) Building construction (m^3)

Land price ($\$/m^2$)	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 is a regression. Flooding is as observed from 2013 to 2020, land prices are from the Jakarta Smart City initiative for 2015, and building construction is from the Global Human Settlement Layer for 2015. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

rather than over a broader set of demographics. This approach avoids the need to measure bilateral migration flows, which is often difficult in granular settings. I estimate $\theta = (\theta_1, \theta_2)$ for $\theta_1 = (\alpha, \phi, \gamma)$ and $\theta_2 = \tau$.

First, fixing θ_2, I match observed and model-implied populations by computing mean utilities $\mu = \{\mu_k\}$ by contraction mapping. Model-implied destination populations are

$$n_k = \sum_j n_j \rho_{jk}(\mu, \theta_2),$$

where computing the right-hand side requires integrating over origin populations n_j. Second, I regress $\hat{\mu}$ on data (r, f, x) to obtain estimates $\hat{\theta}_1$ and residuals $\hat{\varepsilon}$.

$$\mu_k = \alpha r_k + \phi f_k + x_k \gamma + \varepsilon_k$$

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

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

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

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

Empirically, I read destination populations from 2020 data and origin populations from 2015 data. Estimation matches changes from 2015 to 2020 in the distribution of population across space. Uniform population growth rate $\lambda = (\sum_k n_k^{2020})/(\sum_j n_j^{2015})$ augments 2015 populations, such that origin and destination populations balance. Individuals originating at the periphery face distance m_{0k} to destination k, where I define m_{0k} as the minimum distance from k to the core-periphery border.

Euler conditional choice probabilities

The Euler approach compares development in period t to development in period $t+1$. This derivation follows Hsiao (2024a). The goal is to estimate

$$\ln \delta_{kt} - \ln(1 - \delta_{kt}) = \hat{V}_{kt}^1 - \tilde{V}_{kt}^0.$$

The elements on the right-hand side include continuation values, and I derive expressions that instead express these elements in terms of observed data.

$$\hat{V}_{kt}^1 = \frac{1}{2}\omega h_{kt}^2 - \phi f_{kt} - x_{kt}\gamma - \varepsilon_{kt},$$
$$\tilde{V}_{kt}^0 = \beta \mathbb{E}[V_{kt+1}^0] = \beta \mathbb{E}[\hat{V}_{kt+1}^1 - \ln \delta_{kt+1}]$$

The first line is as in the main text. It follows from the first order condition for building height h_{kt} and cost equation 11. Logit shocks give the second line as a special case of Arcidiacono and Miller (2011) Lemma 1. Substituting,

$$\begin{aligned}\ln\delta_{kt} - \ln(1-\delta_{kt}) - \beta\mathbb{E}[\ln\delta_{kt+1}] = & \frac{1}{2}\omega(h_{kt}^2 - \beta\mathbb{E}[h_{kt+1}^2]) - \phi(f_{kt} - \beta\mathbb{E}[f_{kt+1}]) \\ & - (x_{kt} - \beta\mathbb{E}[x_{kt+1}])\gamma - (\varepsilon_{kt} - \beta\mathbb{E}[\varepsilon_{kt+1}]).\end{aligned}$$

By rational expectations, $\mathbb{E}[X_{kt+1}] = X_{kt} + \eta_{kt}^X$ for expectational error η_{kt}^X, which is orthogonal to X_{kt}. Denoting $\Delta X_{kt} = X_{kt} - \beta X_{kt+1}$, I obtain an estimating equation.

$$\Delta\ln\delta_{kt} - \ln(1-\delta_{kt}) = \frac{1}{2}\omega\Delta h_{kt}^2 - \phi\Delta f_{kt} - \Delta x_{kt}\gamma - \Delta\varepsilon_{kt} + \eta_{kt}$$

Hydrological model of flooding

I use machine learning to model 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. Physical models must specify the complex physical processes that contribute to flooding, while machine-learning methods can detect these complexities directly from the data. Mosavi et al. (2018) reviews the machine-learning approach for hydrology, and Jati et al. (2019) offers an example in the Indonesian setting.

As model inputs, I use rainfall, elevation, slope, distances to major rivers, distance to minor rivers, and distance to the coast. Annual rainfall data at a resolution of 4km come from PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) for 2013 to 2020. I compute average annual rainfall. Elevation data at a resolution of 90m come from the Shuttle Radar Topography Mission (SRTM) digital elevation model. I calculate slopes from elevation data by computing slope as the angle of terrain inclination. I compute river and coastal distances with OpenStreetMap data, which distinguish major rivers from streams.

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

I consider a range of models and choose the one with the best fit. Table D1 presents the results. Ensemble methods like random forests, gradient boosting decision trees, and histogram gradient boosting decision trees perform best, as measured by R-squared, mean absolute error, and root mean squared error. As the baseline

Table D1: 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

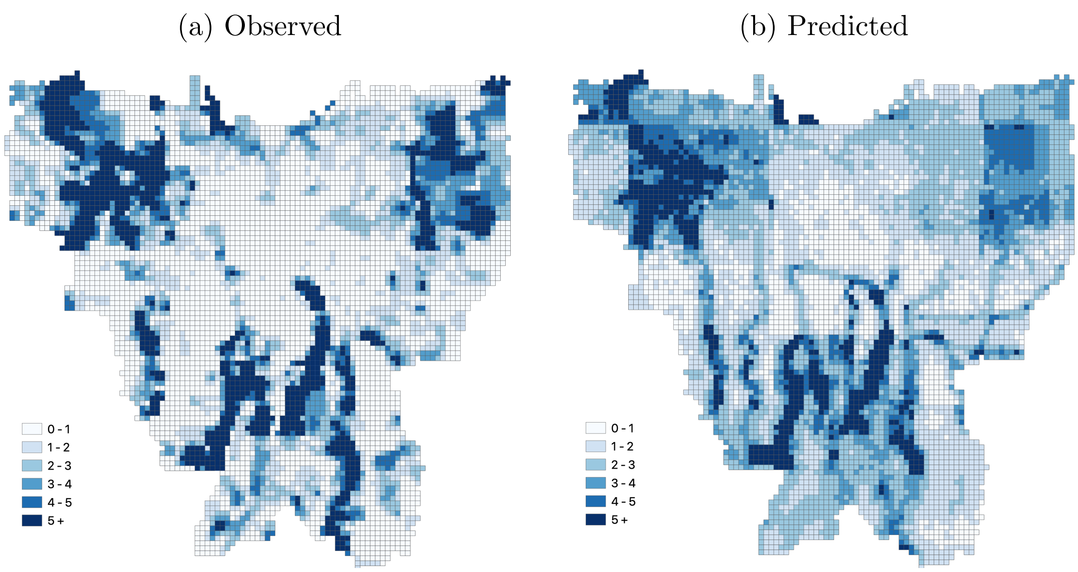
I compute R-squared, mean absolute error (MAE), and root mean squared error (RMSE) with ten-fold cross-validation. Monotonicity constraints apply to distance to major rivers and elevation.

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 D1 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 D2 summarizes feature importance as another means of evaluating the model. I compute permutation feature importance for individual features by shuffling them – adding random noise to their values – and measuring the resulting declines in model fit. The results are sensible, with rainfall, distance to major rivers, and distance to the coast being of primary importance, and distance to minor rivers and slope being less pivotal.

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

Figure D1: Hydrological model fit



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 D2: 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.

E Counterfactuals

E.1 Solving the model

Consider one period and K locations. Residents choose across locations, and developers invest within locations. I distinguish coastal $d_{\text{co}} = \{d_{\text{co},k}\}$ from inland $d_{\text{in}} = \{d_{\text{in},k}\}$, as defense protects the coast. Defense maximizes social welfare.

$$g^*(d) = \arg\max_g \left\{ \sum_k w_k(g; d) \right\}$$

Development does not internalize public costs. With commitment, defense is fixed. Development $d = \{d_k\}$ satisfies market-clearing conditions across locations, with K equations in K unknowns. Without commitment, defense responds to development. Development anticipates this response to force added defense.

$$\begin{aligned} d^*(g) &= \arg\max_d \left\{ \sum_k \pi_k(d; g) \right\} = \{d_k \,|\, P_k^{\text{res}}(d; g) = P_k^{\text{dev}}(d_k)\} \\ d^N &= \arg\max_d \left\{ \sum_k \pi_k(d, g^*(d)) \right\} \end{aligned}$$

Spatial demand introduces computational complexity, as residential value in one location depends on development across locations. I simplify computation in three ways. First, I use gridded interpolation to avoid solving for $g^*(d)$ at each iteration. Second, I apply that defense is coastal to simplify the interpolation grid. Coastal development drives the returns to defense, while inland development enters only through its second-order effect on coastal prices. Thus, $g^*(d)$ is well approximated by $g^*(d_{\text{co}}; d_{\text{in}})$, where I arbitrarily set $d_{\text{in}} = d_{\text{in}}^*$. Third, I apply that defense is coastal to simplify solving for development. If inland development does not affect defense, then it satisfies market-clearing conditions that can be solved quickly.

$$d_{\text{in}}^N(d_{\text{co}}) = \{d_k \,|\, P_k^{\text{res}}(d_{\text{in}}; d_{\text{co}}, g^*(d_{\text{co}})) = P_k^{\text{dev}}(d_k)\}$$

Thus, I can solve over coastal locations rather than all locations.

$$d_{\text{co}}^N(d_{\text{in}}) = \arg\max_{d_{\text{co}}} \left\{ \sum_k \pi_k(d_{\text{co}}, g^*(d_{\text{co}}); d_{\text{in}}) \right\}$$

I then solve for coastal and inland development as a fixed point.

$$d_{\text{co}}^N(d_{\text{in}}) = d_{\text{co}}, \quad d_{\text{in}}^N(d_{\text{co}}) = d_{\text{in}}$$

I apply the same fixed-point strategy when solving over coastal locations. For coastal locations (d_1, d_2) as an example, I solve for each holding the other fixed. I then solve for the fixed point given by $d_1^N(d_2) = d_1$ and $d_2^N(d_1) = d_2$.

Now consider T periods and K locations, with development $d^t = \{d_t, \ldots, d_T\}$ over time, $d_t = \{d_{kt}\}$ over space, and defense $g^t = \{g_t, \ldots, g_T\}$ over time. Defense maximizes social welfare, but development does not internalize public costs. With commitment, defense is fixed. Development satisfies market-clearing conditions in expectation with KT equations in KT unknowns for $k \in [1, K]$ and $t' \in [t, T]$.

$$\begin{aligned}
g^{*t}(d^t) &= \arg\max_{g^t} \mathbb{E}_t[W_t(g^t; d^t)], \\
d^{*t}(g^t) &= \arg\max_{d^t} \mathbb{E}_t[\Pi_t(d^t; g^t)] = \{d_{kt'} \,|\, \mathbb{E}_t[P^{\text{res}}_{kt'}(d^t; g^t)] = \mathbb{E}_t[P^{\text{dev}}_{kt'}(d_{kt'})]\}
\end{aligned}$$

Without commitment, defense responds to development, and development anticipates this response. I solve by backward induction. Period T depends on stocks of past development and defense. For social welfare W_t and coastal welfare Π_t,

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

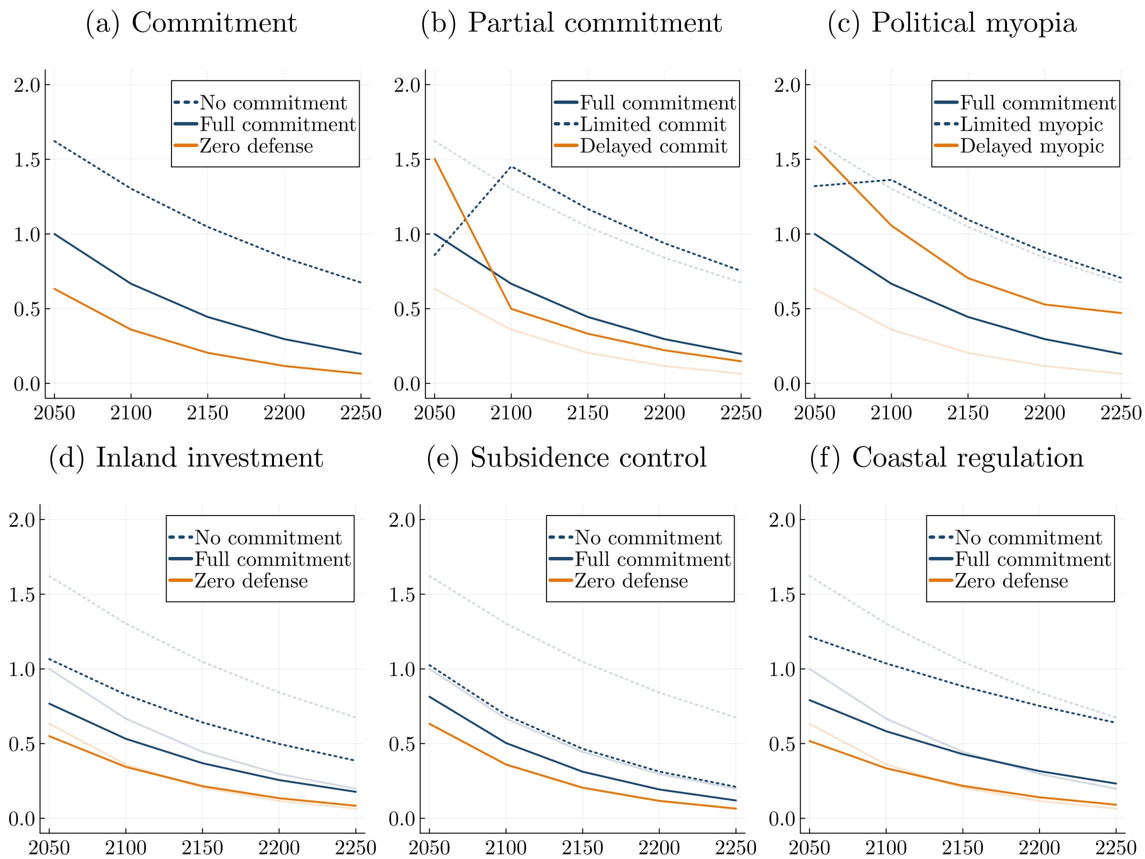
with shorthand $DG_t = (D_t, G_t)$ and stocks $D_t = D_{t-1} + d_t$ and $G_t = G_{t-1} + g_t$. I solve as in the one-period case. Period $T-1$ then anticipates period T.

$$\begin{aligned}
g_{T-1}^N(d_{T-1}) &= \arg\max_{g_{T-1}} \mathbb{E}_{T-1}[W_{T-1}(g_{T-1}, d_T^N(g_{T-1}), g_T^N(g_{T-1}); d_{T-1})], \\
d_{T-1}^N &= \arg\max_{d_{T-1}} \mathbb{E}_{T-1}[\Pi_{T-1}(d_{T-1}, g_{T-1}^N(d_{T-1}), d_T^N(d_{T-1}), g_T^N(d_{T-1}))],
\end{aligned}$$

suppressing dependence on stocks DG_{T-2}. Period $T-1$ affects stocks DG_{T-1} and thus period T. Earlier periods proceed similarly.

E.2 Development

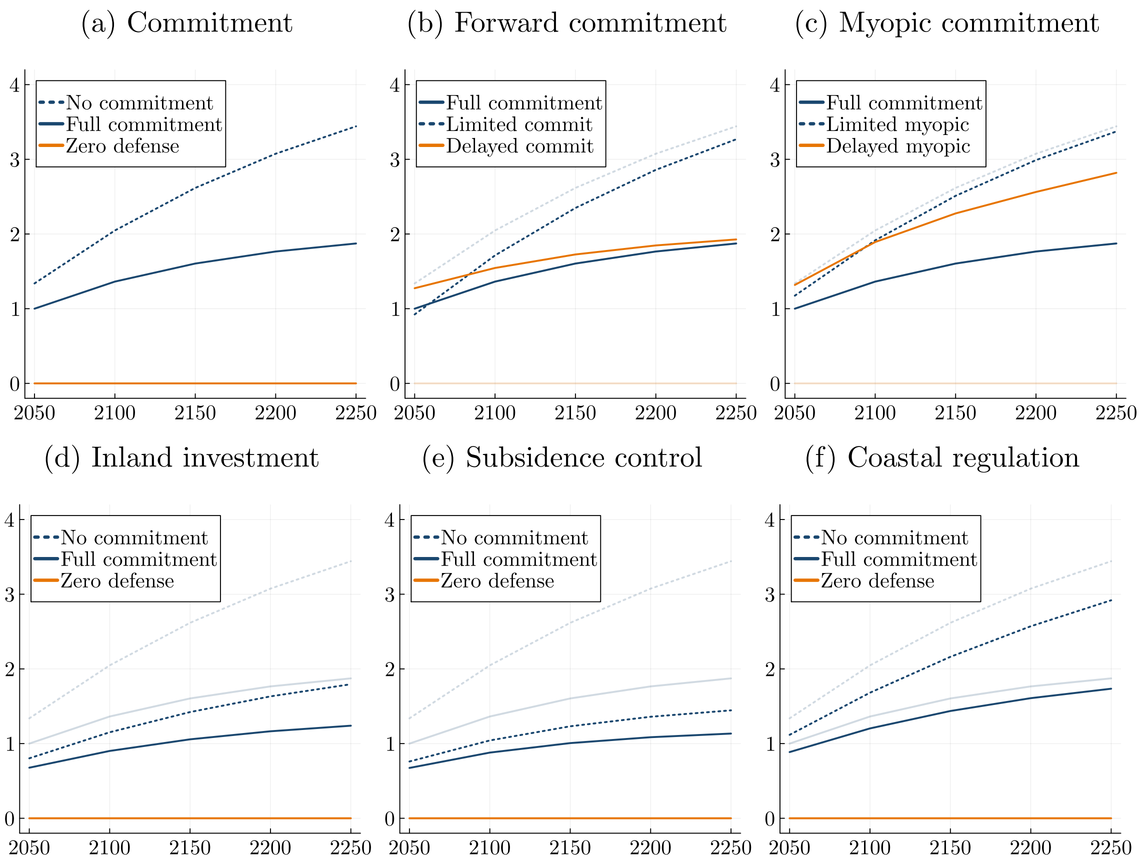
Figure E1: Coastal development over time



Coastal development is new development activity over time in North Jakarta. I normalize by dividing by full-commitment development in 2050. Each curve is one counterfactual. Full commitment chooses defense upfront and adheres to the plan. No commitment chooses defense in a sequential static manner. Zero defense eliminates coastal defense. Limited commitment is full commitment in 2050, then no commitment. Delayed commitment is no commitment in 2050, then full commitment. Under political myopia, governments that act with commitment internalize their own costs of defense but not future costs of defense, which fall instead on future governments. Integrated policy combines coastal defense with inland investment that reduces coastal demand by 25%, subsidence control that slows land subsidence by 25%, or coastal regulation that imposes 25% of the Pigouvian tax. Background lines reproduce the top left figure.

E.3 Defense

Figure E2: Coastal defense over time



Coastal defense is new defense activity over time in North Jakarta. I normalize by dividing by full-commitment defense in 2050. Each curve is one counterfactual. Full commitment chooses defense upfront and adheres to the plan. No commitment chooses defense in a sequential static manner. Zero defense eliminates coastal defense. Limited commitment is full commitment in 2050, then no commitment. Delayed commitment is no commitment in 2050, then full commitment. Under political myopia, governments that act with commitment internalize their own costs of defense but not future costs of defense, which fall instead on future governments. Integrated policy combines coastal defense with inland investment that reduces coastal demand by 25%, subsidence control that slows land subsidence by 25%, or coastal regulation that imposes 25% of the Pigouvian tax. Background lines reproduce the top left figure.

E.4 Robustness

Table E1 considers robustness. Greater discounting reduces the impact of moral hazard over time. More elastic demand and supply increase moral hazard as development responds more strongly to defense. The terminal year makes little difference given discounting. Shorter timing intervals imply more frequent defense and thus more opportunity for moral hazard.

Table E1: Robustness

	Coastal development (2050)		Coastal defense (2050)		Social welfare (NPV)	
Commitment:	Full	No	Full	No	Full	No
Baseline	1.00	1.62	1.00	1.34	14.73	-4.66
Discounting						
$\beta = 0.93$	0.93	1.44	0.96	1.24	6.21	-2.41
$\beta = 0.97$	1.09	1.88	1.05	1.48	33.96	-18.55
Demand						
Price elasticity -25%	0.93	1.45	0.96	1.24	12.50	-0.29
Price elasticity +25%	1.08	1.87	1.05	1.47	17.53	-15.46
Flooding elasticity -25%	1.05	1.86	1.08	1.54	13.91	-21.22
Flooding elasticity +25%	0.91	1.31	0.86	1.05	17.18	10.13
Supply						
Price elasticity -25%	0.95	1.52	0.97	1.28	13.90	-3.58
Price elasticity +25%	1.06	1.74	1.03	1.40	15.64	-6.01
Horizon						
Year 2750	1.00	1.62	1.00	1.34	14.99	-5.11
Year 2300	1.00	1.62	1.00	1.34	15.00	-5.14
Timing						
30-year intervals	1.08	1.88	1.05	1.48	36.40	-23.51
40-year intervals	1.04	1.74	1.02	1.40	22.82	-10.23

Coastal development and defense are new development and defense activity in North Jakarta in 2050. I normalize each by dividing by baseline full-commitment outcomes in 2050. Social welfare is a net present value measured in 1B USD with 2015 dollars, relative to the baseline zero-defense scenario. Each row is two counterfactuals: one under full commitment and one under no commitment. Full commitment chooses defense upfront and adheres to the plan. No commitment chooses defense in a sequential static manner.

E.5 Extensions

Table E2 considers extensions. Political lobbying increases the benefit of development by 25% beyond that relevant for social welfare maximization. Moral hazard worsens as defense becomes more responsive to development. Uncertain flooding involves expectations over a path of future flood risk that varies uniformly from 25% smaller to 25% greater than baseline. Moral hazard worsens as convexity in flood risk makes the expected value worse than the certainty equivalent. Endogenous amenities allow inland amenities to improve as residents migrate inland. I take the distribution of amenities with respect to population as given, then I adjust amenities according to this distribution as migration changes populations in counterfactuals. Moral hazard worsens as the benefit of inland retreat improves. Depreciating development reduces the development stock by 25% each period. Moral hazard worsens as defense becomes more responsive to new development.

Table E2: Extensions

	Coastal development (2050)		Coastal defense (2050)		Social welfare (NPV)	
Commitment:	Full	No	Full	No	Full	No
Baseline	1.00	1.62	1.00	1.34	14.73	-4.66
Political lobbying	1.16	1.96	1.09	1.52	17.19	-8.69
Uncertain flooding	1.01	1.69	1.01	1.38	15.02	-13.78
Endogenous amenities	1.29	2.25	1.16	1.68	19.01	-12.56
Depreciating development	0.86	1.84	0.93	1.46	8.32	-20.02

Coastal development and defense are new development and defense activity in North Jakarta in 2050. I normalize each by dividing by baseline full-commitment outcomes in 2050. Social welfare is a net present value measured in 1B USD with 2015 dollars, relative to the baseline zero-defense scenario. Each row is two counterfactuals: one under full commitment and one under no commitment. Full commitment chooses defense upfront and adheres to the plan. No commitment chooses defense in a sequential static manner.