Sea Level Rise and Urban Inequality

By ALLAN HSIAO*

Sea level rise threatens coastal cities around the world. Will it exacerbate inequality in these already unequal places? The rich may adapt by moving to higher ground, bidding up prices and pushing the poor elsewhere. I study this spatial sorting with a simple quantitative model and granular data from Jakarta, a flood-prone megacity of 32 million. I find that sea level rise will double inequality in flood exposure.

I. Model

Individuals i of wage groups j choose locations k to maximize residential utility.

$$\max_k \{v_{jk} + \varepsilon_{ijk}\}$$

Residential utility includes representative utility v_{jk} and logit taste shocks ε_{ijk}. Locations give representative utility

$$v_{jk} = \alpha_j p_k + \beta f_k + x_k \gamma + \delta_{jk} \tag{1}$$

for housing prices p_k, flooding f_k, observed amenities x_k, and unobserved amenities δ_{jk}. Price elasticities α_j can differ by wage group. Logit shocks imply location choice probabilities

$$\pi_{ijk} = \pi_{jk} = \frac{e^{v_{jk}}}{\sum_\ell e^{v_{j\ell}}}. \tag{2}$$

Individuals within wage groups have common wages and thus common choice probabilities.

In equilibrium, prices $p = \{p_k\}$ clear housing markets in each location.

$$n_k^D(p^*) = n_k^S(p^*) \quad \forall k \tag{3}$$

Housing demand and supply are

$$n_k^D = \sum_i \pi_{ijk}, \quad n_k^S = \bar{n}_k.$$

Demand depends on prices through equations 1 and 2. Equation 2 captures spatial interdependence, as prices in each location affect choice probabilities in every location. Supply reflects fixed capacity $\bar{n}_k$, although a richer model would allow supply to respond more elastically.

Sorting arises from wage-specific price elasticities and endogenous prices. Flood safety is an amenity that commands high prices. The rich accept high prices in flood-safe locations, while the poor may prefer low prices in flood-prone locations. This sorting creates inequality. Sea level rise exacerbates inequality, as it increases demand for flood safety and raises prices in flood-safe locations. The rich crowd out the poor in pursuit of higher ground.

II. Data

I compile fine-grained spatial data for the city of Jakarta. I obtain populations, housing prices, flooding, and geographic variables by 300m cell from Hsiao (2023). Populations for 2015 are from the Global Human Settlement Layer, and housing prices for 2015 are constructed from transaction records and online listings. Flooding for 2013 to 2020 is from city government data, with flood frequency measured in flood days per year. Geographic variables include coordinates, administrative regions, elevation, distance to the coast, and distance to the nearest river.

To study inequality, I construct 2015 populations by wage group for each 300m cell. Full count population census data from 2010 record household addresses. I geocode addresses to cells by extracting information on administrative blocks (*rukun tetangga*), street names, and street numbers. Blocks are very granular, with average populations of 350 people, and enable the direct geocoding of most addresses. The geocoded data cover 84% of 300m cells. I define high- and low-wage groups $j \in \{H, L\}$ by education, as the census data do not directly record wages. I assign individuals with post-secondary education to the high-wage group and those without to the low-wage group. I then compute group shares by cell, and I multiply by 2015 populations to

* Princeton University, Department of Economics, 20 Washington Road, Princeton, NJ 08540, ajhsiao@princeton.edu.
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TABLE 1—WAGES BY EDUCATION

	None	Primary	Middle	High	College
Mean monthly wages (2015 USD)	131	149	182	262	624
Proportion of SUSENAS sample (%)	5	15	17	42	21
Proportion of census sample (%)	16	18	19	35	12

Note: Each column corresponds to a given level of educational attainment. Middle is lower secondary schooling, and high is upper secondary schooling, inclusive of vocational training. College includes all forms of post-secondary schooling. Mean monthly wages are from the 2011, 2012, 2013, and 2014 waves of the SUSENAS socioeconomic survey. These wages measure monthly net income, both money and goods, from an individual's main job. The second row reports educational composition in this sample. For comparison, the third row reports educational composition in the geocoded sample of the 2010 population census.

obtain populations by group-cell.

Table 1 evaluates education as a proxy measure of wages. From the 2011, 2012, 2013, and 2014 waves of the SUSENAS socioeconomic survey, I construct a sample of 26,401 individuals for Jakarta. By comparison, the census data record nearly 10M individuals. The SUSENAS data can be geocoded to the district level, while the census data contain household addresses. But the SUSENAS data record wages, defined as net monthly income from an individual's main job. The table shows that wages increase monotonically with education. I take my high-wage cutoff from the large increase at college education, which includes all forms of post-secondary schooling. SUSENAS wage-earners are more highly educated than the broader population, but estimation and counterfactuals avoid sample selection because they rely only on census data.

III. Estimation

I estimate the model to recover parameters α_j, β, γ, and δ_{jk}. Inverting equation 2,

$$\ln \pi_{jk} - \ln \pi_{j0} = v_{jk} - v_{j0}$$

for reference location $k = 0$. Substituting equation 1, I obtain a linear estimating equation.

$$(4) \quad \Delta \ln \pi_{jk} = \alpha_j \Delta p_k + \beta \Delta f_k + \Delta x_k \gamma + \Delta \delta_{jk}$$

for $\Delta y_{jk} = y_{jk} - y_{j0}$ and $\Delta y_k = y_k - y_0$. With estimated parameters in hand, I can use the model to compute equilibrium prices and choice probabilities under any given pattern of flooding.

I treat 300m cells as locations. For the dependent variable, I compute logged choice probabilities with $\pi_{jk} = n_{jk} / \sum_\ell n_{j\ell}$ and populations n_{jk}, which I observe by wage group and cell. I drop populations of less than 10 individuals, which account for less than 1% of group-cell observations, as logged probabilities exacerbate measurement noise for small populations. For the independent variables, I observe housing prices p_k, flooding f_k, and amenities x_k, which include distance to the coast, distance to the nearest river, elevation, and district fixed effects. These observed amenities act as controls, while unobserved amenities δ_{jk} represent structural errors.

The identification problem is that prices are correlated with unobserved amenities. The reason is sorting: high-amenity locations attract high-wage individuals that bid up prices. I thus require a price instrument. Typical candidates for demand estimation include cost shifters, prices in other markets, characteristics of competing products, and demographics in other markets (Berry and Haile, 2021). My context calls for housing cost shifters, or perhaps housing prices and resident demographics in nearby locations. I choose ruggedness as a cost shifter, as construction must flatten terrain. The exclusion restriction argument is that Jakarta's modest ruggedness is less salient to residents, as it does not impede transportation.

I take flooding as uncorrelated with amenities. In practice, coastal areas may enjoy pleasant coastal views despite elevated flood risk. Conversely, flood-prone areas may suffer from disinvestment in public amenities. Controls help to mitigate this concern. Coastal and river distances control for water amenities, elevation captures pleasant views, and district fixed effects absorb unobserved heterogeneity. At the same time, I find that omitting these controls has limited impact on the estimated flooding coefficient.

I estimate equation 4 by linear IV regression. First, I construct the differenced variables. I

TABLE 2—DEMAND ESTIMATION

	IV		OLS	
	Estimate	SE	Estimate	SE
Log price, low wages	-2.63	(0.45)	-0.15	(0.04)
Log price, high wages	-1.58	(0.61)	0.28	(0.09)
Flooding	-0.09	(0.04)	-0.05	(0.02)
Observations	10,710		10,710	
p-value, low = high	0.01		0.00	
F-statistic	15.50			

Note: Each pair of columns is one regression, and each observation is a group-cell. Groups are low- and high-wage groups, and cells are 300m cells. Prices are 2015 property prices per square meter, measured in units of 1M IDR (roughly 75 USD). The IV specification instruments for log prices with ruggedness. I proxy for wages with education: the high-wage group is those with post-secondary education, and the low-wage group is those without. Flooding is the average number of flood days per year, as observed from 2013 to 2020. Controls include distance to the coast, distance to the nearest river, elevation, and district fixed effects. I report *p*-values for the null hypothesis that low- and high-wage price elasticities are equal.

choose a reference location $k = 0$, and I compute $\Delta \ln \pi_{jk}$ for each wage group. Regressors Δp_k, Δf_k, and Δx_k take the same reference location, but do not vary by wage group. Second, I construct a group indicator, as well as price-group and ruggedness-group interactions. Third, I regress choice probabilities on price-group interactions, flooding, observed amenities, and the group indicator, instrumenting for price-group interactions with ruggedness-group interactions. I obtain $\hat{\alpha}_j$, $\hat{\beta}$, and $\hat{\gamma}$ as coefficients and $\Delta\hat{\delta}_{jk}$ as residuals. I capture δ_{jk} relative to δ_{j0}, but not in levels, noting that the group indicator allows δ_{j0} to vary freely across groups.

Table 2 presents the estimated parameters. IV estimates show that high prices and severe flooding each reduce residential demand. Regressing on log prices allows me to interpret the coefficients as elasticities, and indeed both low- and high-wage groups have elastic demand. But the low-wage group is 66% more price sensitive than the high-wage group, and this difference is statistically significant. Ruggedness serves as a strong instrument, increasing prices in the first stage with an F-statistic of 15.50.

OLS estimates ignore price endogeneity. Because of sorting, locations with high unobserved amenities also have high prices. Individuals may therefore choose these locations despite their high prices. Ignoring this correlation leads to the false conclusion that individuals are not price sensitive. Indeed, OLS estimates exhibit strong upward bias, with inelastic demand for the low-wage group and a positive demand elasticity for the high-wage group.

IV. Sea Level Rise

Will sea level rise exacerbate inequality? I consider relative sea level rise of 1, 3, and 5m for Jakarta. Government plans anticipate 3 to 5m by 2050, citing annual rates of 8mm for global mean sea level rise and 7 to 14cm for local land subsidence (NCICD 2014). The global rate is consistent with scientific estimates, as surveyed by Depsky et al. (2023). The local rates are consistent with older estimates of land subsidence from 1982 to 2010 (Abidin et al., 2011), although newer estimates from 2014 to 2020 are more modest (Tay et al., 2022). Relative sea level rise combines both rates and captures the city's fast march toward inundation.

I project flooding under sea level rise with a simple, elevation-based hydrological model for Jakarta. For relative sea level rise of 1, 3, and 5m, I identify the 1.4%, 6.4%, and 20.5% of 300m cells in my sample that fall below sea level. I assign the maximum flooding observed in the data – 24.5 flood days per year – to these inundated cells, while other cells retain their observed flooding values. These projections capture the spatially heterogeneous impacts of sea level rise, but are likely underestimates. Inundation is certainly worse than 24.5 flood days per year, and I make no adjustment to flooding for cells that fall near sea level, but not below. In ignoring heterogeneity in land subsidence, I

TABLE 3—INEQUALITY WITH SEA LEVEL RISE

	Flooding			Prices
	Low wages	High wages	L/H	L − H
Current	0.88	0.62	1.40	-0.10
Projected				
1m sea level rise	1.03	0.68	1.52	-0.10
3m sea level rise	2.00	0.96	2.09	-0.13
5m sea level rise	5.77	2.20	2.62	-0.22
Projected, no sorting				
1m sea level rise	1.02	0.73	1.39	-0.10
3m sea level rise	1.93	1.32	1.47	-0.11
5m sea level rise	5.47	3.72	1.47	-0.15

Note: The first row computes flood exposure and price incidence from observed data. The first and second columns are flood exposure for the low- and high-wage groups. The third column is the ratio of flood exposure, and the fourth column is the difference in price incidence. The second panel solves the model for equilibrium prices and choice probabilities under projected flooding from sea level rise. Each row is one counterfactual. Prices are normalized against reference location $k = 0$ and can only be interpreted in changes. Flooding can be interpreted in levels. The third panel suppresses the impact of sorting. It computes flood exposure and price incidence with projected flooding and counterfactual prices, but imposes current choice probabilities for each.

also understate inundation in the fast-subsiding north. At the same time, I assume no adaptation via government intervention, which can reduce damages. Hsiao (2023) focuses on this government intervention and its associated challenges.

I calculate flood exposure by wage group j as the average faced by individuals in each group.

$$F_j = \sum_k f_k \pi_{jk} \tag{5}$$

for flooding f_k and choice probabilities π_{jk}. For current exposure, I compute this measure directly from data on current flooding and choice probabilities. For projected exposure, I use the hydrological model to generate projected flooding, then I solve the sorting model for counterfactual choice probabilities.

I solve the sorting model by solving equations 3, which pin down equilibrium housing prices. This system of nonlinear equations can be difficult to solve with many locations. I compute the prices needed to compensate for projected flooding in each location as $p_k' = p_k - \beta(f_k' - f_k)/\bar{\alpha}$, for average price elasticity $\bar{\alpha}$, and I use these non-equilibrium prices as a starting point. I also normalize the price to zero in reference location $k = 0$. Uniform price increases do not affect choice probabilities (absent an outside option), and so normalizing helps avoid multiple solutions. Solving the system gives equilibrium prices, and choice probabilities follow by equation 2.

I focus on the impacts of flooding via housing prices and sorting. In solving the model, I fix wage groups j, amenities x_k and δ_{jk}, and housing supply $\bar{n}_k$ at current levels. It is equivalent to assume that amenities change uniformly across space, that population grows proportionally across wage groups, and that housing supply grows proportionally across locations.

Table 3 presents the results. At current levels, flood exposure is already high and unequal. Both groups experience an average of one flood day every one to two years. But low-wage individuals are more vulnerable, as low-wage exposure is 140% of high-wage exposure. At projected levels, flood exposure increases substantially. Low- and high-wage exposure reaches 5.77 and 2.20 flood days per year with sea level rise of 5m, relative to 0.88 and 0.62 today. Sea level rise also exacerbates inequality. For sea level rise of 1, 3, and 5m, low-wage exposure is 152%, 209%, and 262% of high-wage exposure, relative to 140% today. Inequality nearly doubles in the 5m scenario.

I also calculate price incidence by wage group

j as an average analogous to equation 5.

$$P_j = \sum_k p_k \pi_{jk} \tag{6}$$

for prices p_k and choice probabilities π_{jk}. This measure cannot be interpreted in levels, except when prices are directly observed, because I normalize prices in solving the model. Differencing the low- and high-wage measures eliminates price normalizations, allowing me to compare across scenarios.

Table 3 presents these differenced measures, which I compute with log prices. Sea level rise widens the gap between groups, but now to the benefit of low-wage individuals. The difference of -0.10 today captures lower prices for the low-wage group, and this difference grows to -0.10, -0.13, and -0.22 with sea level rise of 1, 3, and 5m. Lower prices compensate for higher flood exposure, potentially narrowing the welfare gap. The change from 3 to 5m is especially large, as the inundated area expands from 6.4% to 20.5% of cells. The large demand shock induces large price effects.

Lastly, I isolate the role of sorting by conditioning on current choice probabilities. That is, I evaluate equation 5 with projected flooding and equation 6 with counterfactual prices, but each with current choice probabilities instead of counterfactual choice probabilities. For flood exposure, this exercise captures the direct impacts of increased flooding. It offers a simplified evaluation of flood risk that depends only on flood projections, without the need to estimate and solve a sorting model. But in doing so, it assumes immobility and ignores equilibrium responses to sea level rise.

Table 3 shows that inequality is greatly attenuated without sorting. Inequality in flood exposure is stable across scenarios. Low-wage exposure is 139% to 147% of high-wage exposure under sea level rise, relative to 140% today. Inequality in price incidence is similarly attenuated. Thus, it is sorting that drives the impact of sea level rise on inequality. For sea level rise of 5m, sorting reduces high-wage exposure to 2.20 flood days per year, relative to 3.72 without sorting, as high-wage individuals seek out flood-safe areas. It also raises low-wage flood exposure to 5.77 flood days, relative to 5.47 without sorting, as higher prices push low-wage individuals toward flood-prone areas.

V. Conclusion

This paper studies the distributional consequences of sea level rise. I use a simple empirical model to show that sea level rise will exacerbate inequality in flood exposure. Sorting drives this inequality: high-wage individuals seek out flood-safe areas, bidding up prices and pushing low-wage individuals out. For Jakarta, I find that relative sea level rise of 5m will nearly double inequality in flood exposure. Policymakers must navigate these distributional effects as sea level rise reshapes our urban landscapes.

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