Democratization and Infrastructure Investment: Evidence from Healthcare in Indonesia

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Does electoral accountability discipline public spending? After the fall of Suharto, Indonesia held local elections for the first time in decades. I study how this democratization affected the spatial allocation of public investment in healthcare infrastructure. Using the staggered rollout of new hospitals, clinics, and subclinics over time, I estimate a spatial demand system for healthcare that allows me to quantify the surplus generated by any given allocation of facilities. I find that the actual allocation generates only 60% of achievable surplus. Facilities do not go to areas that need them most, especially prior to democratization. To understand why, I model the spatial allocation decision as a dynamic discrete choice problem, and I estimate the government's objective function by revealed preference. On one hand, I find that Suharto-era biases toward certain areas, such as those within the patronage network, are substantially lower after democratization. On the other hand, spillover effects are less internalized as districts become more focused on their own constituents. The first effect dominates, and democratization decreases misallocation overall.

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1 Introduction

Infrastructure investment is at the heart of economic development. The world invests more than $2 trillion each year in infrastructure, and this figure continues to grow (Oxford Economics 2017). But while these investments have long-lasting benefits when allocated efficiently, they are often targets of corruption. Particularly in countries with weak institutions, funds may go missing (Olken 2007) or be distributed by favoritism (Burgess et al. 2015). More broadly, corruption accounts for low economic growth (Mauro 1995). This paper asks whether electoral accountability limits corruption in the context of public infrastructure spending.

I study how the Indonesian government allocated new healthcare facilities – hospitals, clinics, and subclinics – over the last three decades in its efforts to expand healthcare coverage. This expansion spans Indonesia's democratization in 1999, allowing me to compare the allocation of new facilities before and after democratization. To do so, I quantify the welfare effects of new facilities by estimating a spatial model of demand for healthcare. I then model the government's allocation decision as a dynamic discrete choice problem, and I use revealed-preference techniques to estimate how it weighs the benefits of new facilities for citizens against favoritism motives.

The fall of Suharto ushered in democratization with Indonesia's first free elections since 1955, as well as the decentralization of decision-making power from Jakarta to local governments. The result was local electoral accountability, and indeed this bundling of democratization and decentralization is common in other settings as well (Gadenne and Singhal 2014; Mookherjee 2015). While local elections may reduce corruption by increasing electoral accountability, they may also introduce their own distortions as constituents take priority over non-constituents. In particular, there are welfare losses when investments have spillover effects on non-constituents that local governments fail to internalize.

To assess these competing effects, I begin by quantifying the consumer surplus generated by new facilities. I do so by modeling demand for healthcare facilities over space and estimating the model with geocoded panel data on facility access and usage. Conditional on being sick, individuals choose among visiting their closest public hospital, private hospital, clinic, or subclinic, or the outside option of not seeking treatment. They have disutility from the distance and congestion of any given facility, and the staggered rollout of new facilities over time generates panel variation in both. The estimated demand system allows me to compute the consumer surplus generated by any given spatial allocation of facilities.

Next, I evaluate misallocation for each district by comparing consumer surplus under the actual allocation to the maximum achievable with the same budget. Misallocation is zero when the actual and maximizing allocations coincide. I use stochastic optimization techniques to approximate the maximum achievable surplus because the high dimensionality of the solution space makes conventional algorithms intractable. I find relatively large levels of misallocation, particularly before democratization. The actual allocation achieves only 60% of achievable surplus because new facilities do not go to the places that would benefit most.

To understand why, I model the facility placement decision as a dynamic discrete choice problem. The previous analysis relies solely on the demand model, but can only compare misallocation across districts. Additional structure on the supply side allows me to analyze within-district misallocation at the village level. By revealed preference, I estimate the village-level preferences that rationalize the observed deviations from surplus maximization. I then show how these preferences map onto observable village characteristics in line with the channels described above. For estimation, I use moment-inequality techniques that circumvent the high dimensionality of the problem by comparing the actual allocation with a subset of local deviations (Pakes 2010; Pakes et al. 2015; Holmes 2011). This approach simplifies the dynamics of the problem by holding long-term allocations fixed, achieving finite dependence as in Arcidiacono and Miller (2011). I allow placement decisions to depend on unobservables that I accommodate flexibly and allow to vary at a disaggregated level.

My main finding is that democratization decreases misallocation overall. The structural estimates show that Suharto-era biases toward certain areas, such as those within the patronage network, are substantially lower after democratization. At the same time, spillover effects are less internalized as districts become more focused on their own constituents, but this effect is smaller than the first. I also find reduced-form evidence that supports this narrative. For electoral accountability, I use variation in the appointment dates of Suharto-regime district mayors, who were allowed to complete their terms after the Suharto's fall (Martinez-Bravo et al. 2017). Suharto mayors were not subject to electoral accountability – they were all replaced by elected officials – and I find misallocation to be higher in Suharto-mayor districts. For uninternalized spillovers, I use variation in the timing of redistricting, by which districts split into smaller districts (Burgess et al. 2012; Bazzi and Gudgeon 2017). I find no significant effect on district-level misallocation, consistent with only muted distortions from uninternalized spillovers.

I add to a rich literature on democratization and decentralization, reforms that have been central to international development efforts for decades. Seabright (1996) emphasizes voter information in a theoretical model to argue that local elections improve accountability by allowing local issues take center stage. Empirically, Ferraz and Finan (2008) show that voters hold candidates accountable by responding to performance, and Casey (2015) finds that the shift to local elections increases political accountability by empowering voters. This work provides support for the broader finding that democracy facilitates economic growth (Acemoglu et al. 2019). At the same time, decentralized decision-making may be socially suboptimal in the presence of spillovers and economies of scale (Oates 1972). Sigman (2002), Kahn et al. (2015), and Lipscomb and Mobarak (2017) show empirically that uninternalized spillovers result in lower water quality where water flows from one jurisdiction into another. Relative to these papers that focus on particular mechanisms, I provide a unified empirical framework that combines these mechanisms and quantifies the trade-off from a national planning perspective.

I also add to the literature on misallocation by identifying mechanisms underlying the misallocation I observe in the data. Others have identified misallocation across a range of settings: Hsieh and Klenow (2009) for factors across firms, Hsieh et al. (2019) and Bryan and Morten (2019) for labor across occupations and space, and Fajgelbaum and Schaal (2020) and Balboni (2021) for roads across space. Each identifies misallocation by combining data and a model of welfare. Bils et al. (2018) and Rotemberg and White (2021) argue that mismeasured data imply spurious misallocation, but model misspecification has the same effect. I take seriously that deviations from welfare maximization result not from irrationality, but rather a government that maximizes welfare alongside other preferences. I estimate the government objective function to quantify these preferences and how they respond to democratization. I do so for one of the largest healthcare expansion efforts in recent history.

2 Institutional Details

This section describes reforms that followed the end of Suharto's decades-long regime in Indonesia. It also describes the Indonesian healthcare system.

2.1 Democratization

In response to mounting pressure domestic and international pressure, interim president Habibie announced free elections in 1999 – the first since 1955. Previously, Suharto's regime had suppressed opposition parties by forcing them to merge into two parties, one Islamic and one non-Islamic, controlling the opposition leadership, and implementing a recall system that enabled the removal of individual legislators. As a result, between 1973 and 1998 Suharto's party, *Golkar*, won landslide victories in five legislative elections.

District governments are headed by mayors, and under the Suharto regime these mayors were appointed by the central government. Mayors became subject to elections under democratization, but only after the end of the Suharto mayors' five-year terms. Since nearly no Suharto mayor won reelection, these mayors largely operated without electoral concerns. Term end dates varied by district, and Martinez-Bravo et al. (2017) establishes that this variation is quasi-random.[1] Later reforms in 2005 brought the direct election of district mayors.

2.2 Decentralization

Following Suharto's fall, the transitional government passed legislation calling for the transfer of power to local governments (Laws 22/1999 and 25/1999). Decentralization proceeded at a rapid pace and placed district governments at the central of Indonesia's governance structure. Within two years, local district governments received additional authority in the form of two million civil servants, 30% of government expenditures, and responsibility for the provision of a range of public services. Today, district governments perform the majority of administrative functions, particularly as they pertain to the provision of public goods, while the central retains power over issues of national importance, such as foreign affairs and defense.

[1] Data on term end dates come from Martinez-Bravo and Stegmann (2018) and Mukherjee (2016).

After 2001, a number of new district governments were established as existing districts split into smaller districts. I refer to this reform as "redistricting." District governments were required to apply for central government approval to redistrict, and the central government placed a moratorium on redistricting from 2004 and 2006 and again from 2009 to 2012. Burgess et al. (2012) and Bazzi and Gudgeon (2017) argue that the timing of redistricting around the first moratorium is plausibly exogenous.

"Districts" are subdivisions of provinces (*provinsi*) and refer collectively to both regencies (*kabupaten*) and cities (*kota*). Districts are subdivided into subdistricts (*kecamatan*), subdistricts into rural villages (*desa*) and urban neighborhoods (*kelurahan*). These rural villages and urban neighborhoods form the smallest administrative entities in Indonesia, and in this paper I refer to both as "villages." In sum, the administrative hierarchy is as follows: nation, province, district, subdistrict, and village.

2.3 Healthcare

The public healthcare system is layered

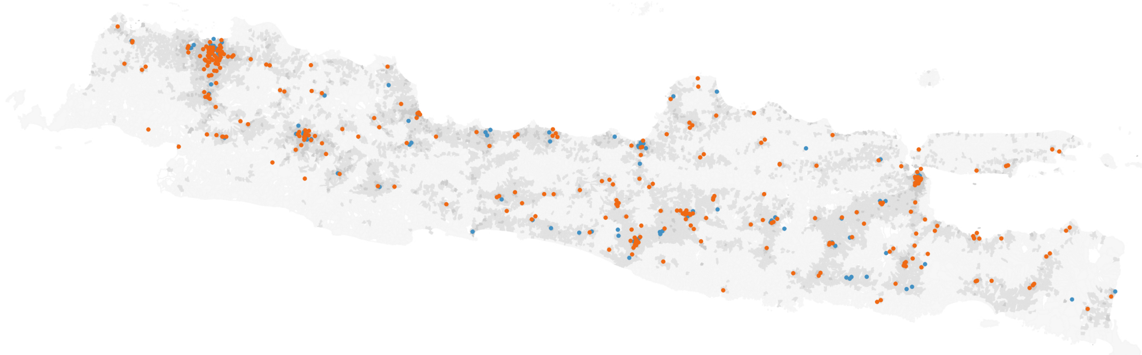
The public system consists of hospitals, clinics, and smaller facilities. Hospitals are themselves divided into classes: class A hospitals average 1,450 beds and cover a range of specialties, while class D hospitals are district-level facilities that average 70 beds and offer only general care. Below hospitals are clinics (*puskesmas*), which are usually staffed by a physician and focus on providing primary care. Some clinics are equipped to provide basic inpatient services. Clinics are further supported by a network of subclinics (*pustu*) and village facilities, including village health posts (*poskesdes*), village maternity posts (*polindes*), and neighborhood health posts (*posyandu*). Subclinics are staffed with one to three nurses and visited weekly to monthly by a physician. Village facilities are often staffed by local volunteers trained by health workers and may operate on borrowed premises.

Access expanded with infrastructure

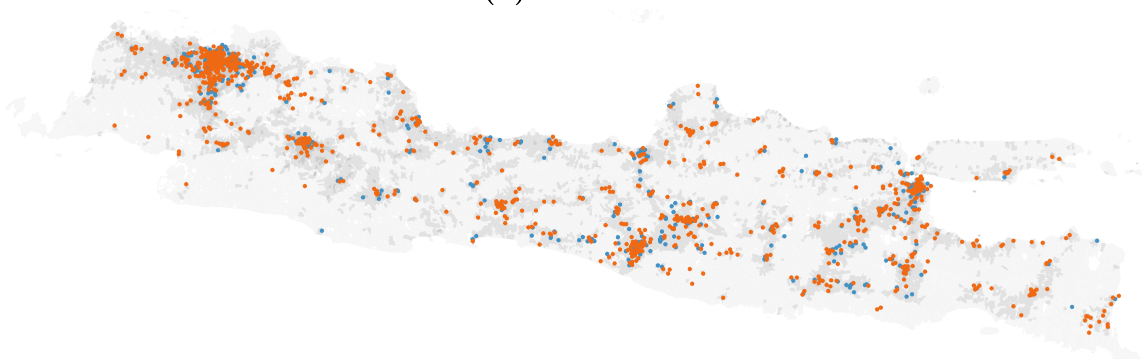
The Indonesian government has expanded access to healthcare services by devoting significant resources to building infrastructure. Since the origins of the clinic system in the 1970s, the government has worked toward its formal goal of one clinic per 30,000 people or subdistrict, and one subclinic per 10,000 people. In the 1990s,

Figure 1: Hospitals versus population density in Java, 1990-2014

(a) Java 1990



(b) Java 2014



Orange dots are public hospitals, blue dots are private hospitals, and gray shading conveys population density. There are 390 hospitals in 1990 and 1,258 in 2014. Expansion seems strongest in areas of initial concentration and high population density – the cluster to the northwest is Jakarta. Data are from PODES.

the government implemented the *Bidan di Desa* initiative, which sought to station a midwife in every village. At the same time, figure 1 shows the visible expansion of hospitals since 1990 for Java, Indonesia's most populous island. Today, there are about 2,500 hospitals, 10,000 clinics, and 25,000 subclinics nationwide.[2]

Under decentralization, district governments place new facilities

Before decentralization, the central government funded facility construction and possessed broad authority over the placement of new facilities. The clinic system, for example, was originally funded by the same INPRES program that funded the large-

[2] The Indonesian government has also expanded insurance coverage, launching universal healthcare (JKN: *Jaminan Kesehatan Nasional*) in 2014. This program builds on the *Askeskin* (2004) and *Jamkesmas* (2008) programs, which provided coverage to the poor and near poor.

scale construction of more than 60,000 schools in the 1970s. Later, central funding continued through the Ministry of Health.

Since decentralization in 2001, district governments have been responsible for the direct implementation of healthcare services. Funding continues to come from the central government, including through disbursements from the Special Allocation Fund (*Dana Alokasi Khusus*) that are earmarked for facility construction. District governments negotiate with the central government for funds, including with proposals for new facilities, but the central government cannot enforce agreed-upon proposals and can even have limited information on the completion status of funded projects. That is, it is district governments that choose the placement of budgeted facilities.

The private system primarily serves the wealthy

Private hospitals cater to the wealthy and operate outside of the public system. Growth in the number of private hospitals has largely involved the establishment of smaller, single-specialty hospitals – particularly in dentistry. Private doctor practices (*praktek dokter*) and polyclinics (*poliklinik*) are the private counterparts to public clinics and often result from public doctors who open secondary practices. These facilities also serve relatively wealthy clientele, although less so than private hospitals.

3 Data

Village-level data on health infrastructure come from the Village Potential Statistics (PODES), a census of Indonesian villages conducted every few years. I use data from 1990 to 2014, and I merge the data over time using village locations. The core data cover hospitals, clinics, subclinics, and village-level facilities, and record the number of facilities for each type by village. In 2011, the data contain information on facility quality for clinics, subclinics, and village-level facilities. The PODES data also contain village-level voting results in the 1999 and 2004 legislative elections. The PODES data do not distinguish between public and private hospitals, so I also draw on Rumah Sakit Online (RSO), an online database of hospitals maintained by the Indonesian Ministry of Health. This database lists approximately 2,500 hospitals and contains information on address, type (public or private), number of beds, number of personnel, and some measures of hospital quality. I use the RSO distinction between

Table 1: Summary statistics by year (PODES)

Year	1990	1993	1996	2000	2003	2006	2008	2011	2014
Public hospitals	664	750	798	863	942	1,084	1,279	1,526	1,840
Private hospitals	231	260	282	307	351	395	465	544	654
Clinics	5,202	6,021	6,435	6,868	7,199	7,719	8,533	9,398	10,788
Subclinics	12,412	15,660	17,140	19,154	20,196	21,480	23,217	24,767	27,744
Distance, public hospital	30.58	28.71	28.36	27.43	26.21	23.91	21.51	19.72	18.32
Distance, private hospital	66.22	65.78	64.63	63.17	61.69	59.36	56.36	53.60	50.83
Distance, clinic	6.95	6.32	6.07	5.75	5.49	5.17	4.68	4.34	4.07
Distance, subclinic	4.21	3.46	3.18	2.79	2.63	2.47	2.25	2.07	1.81
Congestion, public hospital	442.83	424.52	418.10	374.01	363.22	328.79	296.96	258.44	225.54
Congestion, private hospital	1,274.83	1,280.61	1,261.05	1,127.77	1,087.34	1,035.04	984.82	929.34	811.11
Congestion, clinic	38.13	33.90	32.41	29.67	29.89	29.11	28.54	27.04	25.28
Congestion, subclinic	25.97	20.44	19.30	16.77	16.67	16.41	16.42	16.41	15.21
Rural (dummy)	0.89	0.89	0.89	0.89	0.82	0.81	0.82	0.81	0.81
Population	2,901	3,026	3,090	3,022	3,199	3,325	3,529	3,682	3,776
Area (km^2)	26.69	26.69	26.69	26.69	26.69	26.69	26.69	26.69	26.69
Observations	62,194	62,194	62,194	62,194	62,194	62,194	62,194	62,194	62,194

Each observation is a village. The first four rows are totals, and all other rows are averages. Distance is to the closest facility of a given type and is measured in kilometers. Congestion is of the closest facility of a given type and is measured as the number of people (in thousands) for whom this facility is the closest of its type.

public and private hospitals in 2016 to classify hospitals in the PODES data.

The National Socioeconomic Survey (SUSENAS) dataset contains annually collected, individual-level data on healthcare usage by facility type. Unlike the PODES data, these data do distinguish between public and private hospitals. The data also contain demographic information and a limited set of health outcomes. Data with village-level locations are available from 1993 to 2010. Village locations allow me to link the data over time, as well as to the PODES data. Furthermore, villages are sufficiently small that I can geocode the data and calculate distances between individuals and facilities with a relatively high degree of accuracy.[3]

Table 1 summarizes the village-level data by year. For the more than 62,000

[3] An empirical concern is that, within a district, most hospital construction occurs in the district capital. With a dataset coded at the city level, one would therefore struggle to find any location effects if hospitals were always built in the same city. Within a city, however, there are many neighborhoods, and data geocoded at the village level are capable of detecting shifts toward certain neighborhoods over others.

villages for which I was able to construct a balanced panel, the number of facilities has grown over time for all facility types. The panel data cover a tripling of hospitals from 1990 and a doubling of clinics and subclinics. Consistent with this growth, facility distance and congestion has declined.

4 Welfare

This section quantifies welfare effects with a model of spatial demand for health-care facilities. I specify the individual's choice problem and discuss estimation.

4.1 Model

An individual seeks care at a facility type $f \in \mathcal{F}$, where the choice set $\mathcal{F}$ contains public hospitals, private hospitals, clinics, and subclinics. I assume that individuals consider the closest facility of each type because the data record usage by facility type, but not by specific facility within a type. The utility of facility type f for individuals living in village v at time t is

$$\text{utility}_{fvt} = \underbrace{x_{fvt}\beta_f + \alpha p_{fvt} + \xi_{ft} + \delta_v + \delta_t}_{\equiv V_{fvt}} + \varepsilon_{fvt} \, .$$

Individuals consider facility characteristics $x_{fvt} = [\text{distance}_{fvt}, \text{congestion}_{fvt}]$, and I allow these preferences to vary by facility type. Individuals also consider facility prices p_{fvt}, which I observe, and facility quality ξ_{ft}, which I do not observe. This specification restricts facilities to be homogeneous within a given facility type and year. Parameters δ_v and δ_t are village and time fixed effects, and ε_{fvt} are logit errors. I normalize the utility of the outside option to zero. The logit inversion implies

$$\ln(s_{fvt}) - \ln(s_{0vt}) = x_{fvt}\beta_f + \alpha p_{fvt} + \xi_{ft} + \delta_v + \delta_t + \epsilon_{fvt} \, , \tag{1}$$

where s_{fvt} denotes market shares by facility type, village, and year. I also consider a specification with population-density interaction $(x_{fvt} \cdot \text{popden}_{vt})\beta'_f$ that allows preferences to vary between rural and urban villages, as well as facility quality ξ_{ft} that varies freely between villages with above- and below-mean density.

4.2 Estimation

I calculate market shares from individual-level data on the number of visits to each facility type in the last month. I focus on the period from 1993 to 2002 because the SUSENAS data do not distinguish between clinic and subclinic visits in other years. For each sick individual, which I define as those reporting at least one health concern, I classify the individual as having visited either a private hospital, public hospital, clinic, or subclinic. For individuals who visited multiple facility types, I code them based on the most expensive facility type they visited (in order, private hospital, public hospital, clinic, and subclinic). The alternative is to compute market shares by visits instead of by individuals as I do here, but this alternative approach would treat visits as independent. Since I focus on sick individuals, the outside option is choosing not to visit a facility despite being sick. Lastly, a practical concern is that the logit inversion is infeasible when market shares are zero or one, so I use inverse-distance weighting to smooth the market shares that I estimate from the data.

For facility characteristics, I measure distances as Euclidean distances between village centroids. Congestion is a function of how many individuals use a given facility. I proxy for this measure with the number of individuals for whom a given facility is the closest facility of its type. In the language of Donaldson and Hornbeck (2016), distance_{fvt} captures the direct effects of facility construction, while congestion_{fvt} captures the indirect effects. That is, a new facility directly increases usage in nearby villages by decreasing travel distance, and also indirectly increases usage in faraway villages as movement to the new facility decongests other facilities.

I construct prices from household-level data on health spending. For each village and year, the following regression of spending on visits yields the average amount of money spent on each facility type (or the outside option).

$$\text{spending}_{hvt} = \mu_{0vt} + \mu_{fvt} \sum_{f \in \mathcal{F}} \text{visits}_{fhvt} + u_{hvt}$$

To ensure prices are smooth over space, I run the regression for each village using data from all villages, using inverse-distance weights $(1+\text{distance}(v, v'))^{-2}$ that weigh nearby villages more heavily. I obtain variation in prices over time by repeating this procedure for each year in the data.

Table 2: Usage by facility distance and congestion

	Estimate	Standard Error
Distance, public hospital	-2.295***	(0.0561)
Distance, private hospital	-1.127***	(0.0323)
Distance, clinic	-2.456***	(0.233)
Distance, subclinic	-2.404***	(0.442)
Congestion, public hospital	-0.0247***	(0.00298)
Congestion, private hospital	-0.0172***	(0.00127)
Congestion, clinic	-0.381***	(0.0389)
Congestion, subclinic	-0.589***	(0.0246)
Price	-0.537***	(0.152)
Village FE	x	
Facility type-year FE	x	
Observations	202,668	

Each column is a single conditional multinomial logit regression with village and facility type-year fixed effects. The unit of observation is a village-year-facility type, where the set of facility types represents a village's choice set in a given year. The outcome is usage by facility type, as recorded in the SUSENAS data. Distance is to the closest facility of each type and is measured in units of 100 km. Congestion of the closest facility is the number of people for whom this facility is the closest of its type. This variable is measured in units of 100,000 people. Price is measured in units of $100 (in year 2000 USD). Additional controls include population and ruralness. Standard errors are clustered by village. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3 Estimates

I estimate specification 1 by OLS and present the resulting estimates in table 2. Facility distance and congestion correspond to lower usage, and demand for clinics and subclinics is more elastic than demand for public hospitals. Demand for private hospitals is least elastic. In the appendix, figure A1 plots the raw correlation between usage and distance, and figure A2 shows the lack of pretrends. Table A1 shows relatively little heterogeneity by population density. Urban areas are more elastic in terms of distance and less elastic in terms of congestion, although only the congestion differences are statistically significant. Thus, in the next stage of analysis I focus on the non-interacted demand estimates of table 2.

One concern is that the price coefficient is biased because the price data are constructed and therefore subject to potentially substantial measurement error. In practice, in the analysis that follows I only use the price coefficient to denominate the demand system's utility predictions in dollar terms. Alternatively, I can use the distance coefficients to denominate utility in terms of kilometers saved. Indeed, comparing the magnitudes of the price and distance estimates suggests that patients value one kilometer saved at approximately $4, a figure that is perhaps high but nonetheless within range of a sensible prior.

4.4 Extensions

Future work will focus on the following extensions to this simple model of demand. First, I can avoid the issue of price endogeneity by using travel time in place of distance and price, and using a valuation of time to monetize the system. Since the SUSENAS data record incomes, the valuation of time could be allowed to vary by individual. Second, I follow the spatial demand literature by taking distance as exogenous, but a more sophisticated approach could instrument for distances using the distance-minimizing allocation, which is similar to the least-cost-path approach commonly adopted in work on transportation networks. Third, I can allow distance and congestion elasticities to vary with individual characteristics in a random-coefficients framework. This added flexibility would allow welfare effect to differ, for example, between rich and poor villages. Fourth, I restrict heterogeneity among facilities by imposing homogeneity within a facility type and year, but I can relax this restriction by allowing for heterogeneity by region or with grouped fixed effects. The data also contain some observables on hospitals and clinics that I can control for directly. Fifth, I restrict village heterogeneity to a village fixed effect and a time fixed effect, but I can also allow for differential time trends by village. Sixth, clinics provide referrals to hospitals for serious conditions, and I can capture this interaction by allowing complementarities across facility types.

5 Misallocation

The estimated demand system allows me to quantity the surplus generated by any given allocation of healthcare facilities. This section proposes a measure of misallocation that compares the surplus generated by observed allocations to the maximum achievable under the same budget constraint.

5.1 Consumer surplus

Consumer surplus is a function of the compensating variation associated with a given facility placement. Defining notation, let policy a specify where facilities are built over time. Placement a^t is the allocation of facilities resulting from policy a as of time t. As in McFadden (1981), I use the estimated price elasticity $\widehat{\alpha}$ to calculate the change in prices needed to compensate for some change in facility characteristics. Defined in relation to benchmark $\underline{a}^t$, the compensating variation associated with moving to placement a^t is

$$CV_{vt}(a^t, \underline{a}^t) = \frac{1}{\widehat{\alpha}}\left[\ln\left(\sum_{f\in\mathcal{F}}\exp\big(V_{fvt}(a^t)\big)\right) - \ln\left(\sum_{f\in\mathcal{F}}\exp\big(\underline{V}_{fvt}(\underline{a}^t)\big)\right)\right]. \tag{2}$$

V_{fvt} are fitted values from specification 1, and $\underline{V}_{fvt}$ can be calculated as

$$\underline{V}_{fvt} = V_{fvt} + \big(\underline{x}_{fvt} - x_{fvt}\big)\beta_f\,,$$

where x_{fvt} and $\underline{x}_{fvt}$ are distance and congestion under placements a^t and $\underline{a}^t$, respectively, assuming that a change in facility placement does not impact pricing.[4] The consumer surplus gains arising from placement a^t are therefore

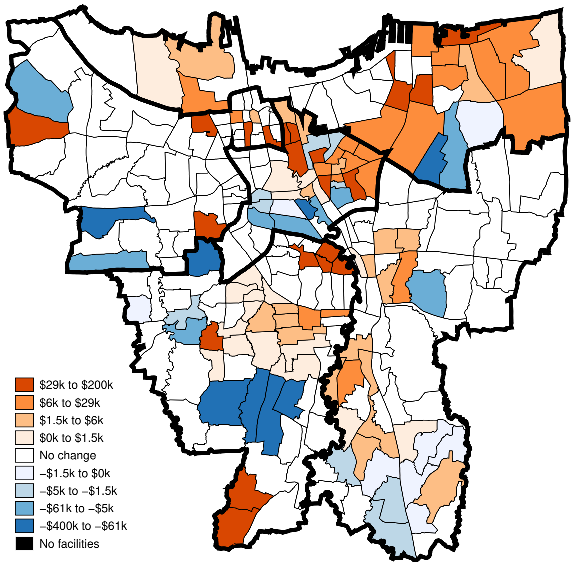
$$\Delta\,\text{surplus}_t(a^t, \underline{a}^t) = \sum_{v\in\mathcal{V}} \text{population}_{vt}\cdot CV_{vt}(a^t, \underline{a}^t)\,,$$

and gains from a policy over time are

$$\Delta\,\text{surplus}(a, \underline{a}) = \sum_t \beta^{t-1}\Delta\,\text{surplus}_t(a^t, \underline{a}^t)\,.$$

[4] To obtain values for V_{fvt}, I extrapolate from the usage sample, which covers a subset of villages from 1993 to 2002, to other villages and other years. As such, calculating the fitted values requires some imputation of village fixed effects δ_v and year fixed effects δ_t. For out-of-sample villages in districts with at least 10 in-sample villages, I impute the village fixed effect as the distance-weighted average of the same-district, in-sample fixed effects. I use the same weighting scheme as when I smooth the choice probabilities, namely $(1+\text{distance}(v,v'))^{-2}$. For the small proportion – about 0.5% – of out-of-sample villages in districts without at least 10 in-sample villages, I calculate the distance-weighted average of all in-sample fixed effects. For year fixed effects, I use the year 1993 fixed effect for pre-1993 years and the year 2000 fixed effect for post-2000 years.

Figure 2: Surplus under maximizing vs. actual placement, Jakarta



This figure plots compares villages' consumer surpluses under the surplus-maximizing and actual placements. In Jakarta, the administrative unit of a "village" can be thought of as a neighborhood. Villages in orange gain under the surplus-maximizing allocation, while villages in blue lose. That there are more orange villages reflects that total surplus under the surplus-maximizing allocation is larger than that under the actual allocation.

Note that the use of benchmark $\underline{a}$ is necessary because, as is typical of discrete choice models, consumer surplus is identified in changes but not in levels.

5.2 Surplus-maximizing allocation

Consider the allocation $\bar{a}$ that maximizes consumer surplus gains for society subject to the same construction budget over time as in observed placement a.

$$\bar{a} \equiv \arg\max_{b} \Delta\,\text{surplus}(b, \underline{a}) \quad \text{s.t.} \quad \sum_{v \in \mathcal{V}} n_v(b^t) = \sum_{v \in \mathcal{V}} n_v(a^t) \quad \forall\, t\,, \tag{3}$$

where $n_v(\cdot)$ is the number of facilities in village v resulting from a given placement. Figure 2 compares the surplus-maximizing and actual allocations for Jakarta. Here, the problem is of relatively low dimension, and I can solve for the surplus-maximizing allocation exactly. More generally, obtaining this allocation requires solving an NP-hard combinatorial optimization problem. The solution space expands exponentially in the number of villages, the number of facilities, and the number of time periods.

At the national level, the problem is intractable.

I make progress in two ways. First, I solve the problem locally at the district level, and I aggregate these sub-solutions to approximate the full solution. This local approach will differ from the full solution when cross-district spillover effects are large, so to mitigate this bias I account for these out-of-district spillover effects by specifying the local subproblems over a given district and a surrounding buffer zone. I choose the buffer zone to include any out-of-district village that would potentially be impacted by construction in the district of interest, whether it be through distance or congestion reductions. In this way, I account for any interaction between new construction in a district and the existing facilities in neighboring districts. However, the interaction between new in-district construction and new neighboring-district construction may still generate some bias.

Second, I apply simulated annealing to solve the problem heuristically. Simulated annealing is a stochastic, global optimization algorithm that is a variant of Metropolis-Hastings. I specify a starting temperature high enough to accept at least 95% of proposal solutions. The algorithm stops when the best candidate solution has not been surpassed for 500 iterations, and when the acceptance ratio is no higher than 5%. For robustness, I repeat the algorithm from 5 random starts and take the best solution. This algorithm breaks the curse of dimensionality, and I find that it performs consistently over the multiple starts in my setting.

This class of stochastic algorithms is not commonly used in estimating structural parameters because they do not deliver the exact solutions that gradient-based local optimizers do. The concern is that candidate solutions can differ substantially from the true solution but nonetheless be identified as optimal because they achieve similar objective values. For example, suppose a function is maximized by true parameters $\theta = (1, 10)$ with objective value $f(\theta) = 100$, and a stochastic algorithm delivers an estimate $\hat{\theta} = (10, 1)$ with objective value $f(\hat{\theta}) = 99.9$. This discrepancy can be a problem if the goal is to interpret the parameter estimates themselves, but it is not a problem if the quantity of interest is the objective value itself. Indeed, stochastic algorithms are more common in machine learning applications where the focus is on prediction and not on the interpretation of coefficients. Similarly, my measure of misallocation is only a function of the (approximately) maximized objective value $\Delta\text{surplus}(\bar{a}, \underline{a})$ and not the maximizing allocation.

5.3 Measuring misallocation

In particular, my measure of misallocation compares the consumer surplus generated by the observed allocation to that of the surplus-maximizing allocation.

$$\text{misallocation}(a, \underline{a}) = 1 - \frac{\Delta\, \text{surplus}(a, \underline{a})}{\Delta\, \text{surplus}(\bar{a}, \underline{a})} \tag{4}$$

This measure of misallocation is in percentage terms and is zero when the observed and surplus-maximizing placements coincide. As in Asker et al. (2019), it captures the difference between achieved and achievable results. For each district, I evaluate the time profile of misallocation by computing this measure for each three-year period t. Although I compute consumer surplus gains by district, the optimal placement is defined as that which is optimal for society – namely, the placement that fully internalizes the spillovers to non-constituents living outside of a district's borders.

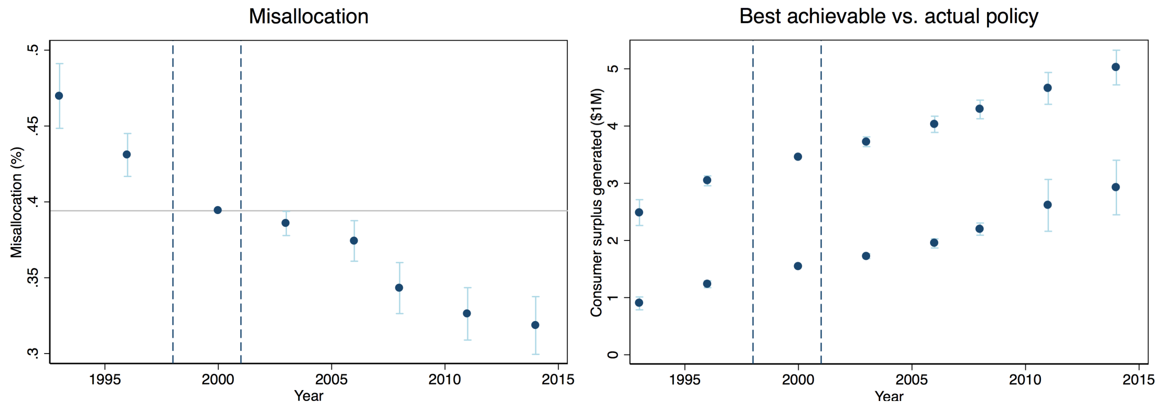
Figure 3 shows how, on average, these values evolve over time. The left panel shows that misallocation levels are lower after the reform period. The data cover a relatively short period of time before the reform, so future work will focus on collecting additional data to extend the length of the panel. The right panel shows the estimated consumer surplus gains that I use to estimate misallocation.[5] The dashed line shows the maximum consumer surplus gains achievable under the budget constraint, while the solid line shows those achieved by the observed placements. For all years I take facility placements in 1990 as the benchmark placement, and as such these figures present the time path of the stock of misallocation. In the appendix, figures A3 and A4 show the contribution of each facility type to these trends. In these calculations, I optimize over each facility type in turn while holding the other facility types fixed. Clinics contribute most to overall misallocation, and public hospitals least.

5.4 Challenges in interpreting misallocation

Interpreting this measure of misallocation requires some caution. In general, any quantification of misallocation is dependent on a economic model, which either

[5] To see why the misallocation figures are not exactly determined by dividing the solid line by the dashed line, note that misallocation first divides the actual by achievable gains, then takes the average, while dividing the solid and dashed lines would take the average of the actual gains and the average of the achievable gains, then divide them.

Figure 3: Misallocation over time



Misallocation is defined as one minus the proportion of the maximum achievable consumer surplus gain that is achieved by the observed placement. It is zero when the actual placement coincides with the surplus-maximizing placement. The plot on the right shows the consumer surplus generated by the surplus-maximizing placements (top line) and the actual placements (bottom line) over time, controlling for district fixed effects. For each period, the benchmark placement $\underline{a}$ is the facility placement in 1990. The vertical dashed lines mark the period of reform, and the error bars are 95% confidence intervals.

delivers an optimal allocation directly or shows that marginal products are unequalized across agents (and therefore that the current allocation is suboptimal). This dependence on a model means that model misspecification will spuriously suggest misallocation. For example, building on the seminal quantification of firm-level factor misallocation in Hsieh and Klenow (2009), Bartelsman et al. (2013) and Asker et al. (2014) discuss how a model with adjustment frictions can explain a significant portion of the productivity dispersion observed among firms.

Applied to misallocation in infrastructure investment, these insights suggest that the level of misallocation I find in figure 3 can change depending on how I specify the benchmark objective function. That is, the question of what agents are maximizing is central to measuring misallocation. I find that facilities are about 40% misallocated relative to an allocation that maximizes consumer surplus. But another objective function may place weight on equity over space, and yet another objective function may value gains to the wealthy, who have higher willingness to pay. Measured against these benchmarks, misallocation may be higher or lower than 40%. As such, while papers like Fajgelbaum and Schaal (2020) and Balboni (2021) make significant progress in quantifying misallocation under an assumed government objective function, these exercises are not geared toward determining whether the misallocation they measure is a result of irrational behavior or simply a government objective function that differs from the ones used in their models. Instead, it is the changes over time that deserve emphasis, as these changes are all measured relative to the same benchmark.

A potential confounder of the changes over time seen in figure 3 is misspecification of the agent's dynamic horizon – another example of model misspecification. The concern is that a forward-looking government will make facility placement decisions accounting for future placements, such that placements that look suboptimal today are in fact optimal given placements in subsequent periods. Any misspecification of how far the government looks into the future will therefore be spuriously attributed to misallocation. Appendix figure A6 further illustrates this concern with a simple example. The revealed-preference approach I take in the following section remains subject to this concern, so planned work will check robustness across different assumptions on how forward-looking the government is.

Another potential confounder is mismeasurement. Bils et al. (2018) and Rotemberg and White (2021) document how mismeasurement of data can be attributed to misallocation across firms. In this setting, improvements in survey technology over time will generate a decrease in measured misallocation over time simply because optimal allocations in earlier periods are incorrectly recorded as suboptimal allocations. It is difficult to credibly rule out this possibility for the purposes of figure 3, but the revealed-preference approach that I take in the following section is robust to this concern.

6 Determinants of Misallocation

This section seeks to explain observed misallocation. It models the facility placement problem as a dynamic discrete choice problem and estimates the government's objective function by revealed preference.

6.1 The facility allocation problem

I consider the dynamic facility location problem at the level of the district. At time $t = 0$, the district mayor chooses a policy a that specifies where to build facilities in every future period. The mayor chooses construction locations, but is subject to a budget constraint that specifics the number of facilities to be constructed in each period. Recall that a^t denotes the placement resulting from policy a as of time t, and $n_v(a^t)$ the number of facilities in village v given placement a^t. The mayor's objective function is a discounted sum of payoffs over time.

$$\pi(a) = \sum_{t=1}^{\infty} \beta^{t-1} \Big(S(a^t) + X(a^t) + \xi(a^t) \Big) \tag{5}$$

It nests maximization of consumer surplus S, which I used to define measure misallocation in section 5, but it can also include other preferences – both observed X and unobserved ξ.

The mayor considers the consumer surplus generated by a given placement. I set social surplus as the numeraire, and I distinguish between surplus for in-district and out-of-district villages.

$$S(a^t) = \sum_{v \in \mathcal{V}_{\text{in}}} \text{surplus}_{vt}(a^t;\, \omega) + \underbrace{\sum_{v \in \mathcal{V}_{\text{out}}} \tau^S \text{surplus}_{vt}(a^t;\, \omega)}_{\text{internalized spillovers}} \tag{6}$$

Consumer surplus is a function of the demand system estimated in section 4, and as such depends on demand parameters ω. Patients can travel, so villages can benefit from new facilities even if they do not receive the facilities themselves. The parameter $\tau^S \in [0, 1]$ captures the extent to which a mayor internalizes spillover benefits for out-of-district villages. At one extreme, a mayor that acts as the social planner does internalizes spillovers fully, such that $\tau^S = 1$. At the other extreme, a mayor focusing on in-district villages will fully discount spillover benefits to out-of-district villages, which provide neither votes nor tax revenue, such that $\tau^S = 0$. A richer model could allow for more nuanced internalization of spillovers, such as among neighboring districts headed by mayors of the same political party.

I consider the extent to which observables can rationalize deviations from surplus maximization. In particular, the mayor's decision may also be subject to favoritism.

$$X(a^t) = \sum_{v \in \mathcal{V}_{\text{in}}} \sum_{f} n_{fv}(a^t) \cdot D_v \bigg(\underbrace{\tau_f^P \text{patronage}_v + \tau_f^G \text{golkar}_v + \tau_f^E \text{ethnicity}_v}_{\text{favoritism}} \bigg) \tag{7}$$

Favoritism includes the military patronage network and a village's underlying support for the *Golkar* party, both of which potentially give rise to distorted allocations under the Suharto regime. I also include ethnic composition, which is another source of favoritism in this context. I sum over in-district villages because the mayor considers only in-district placements, and I allow for differential impacts by facility type $f \in \{\text{hosp, clin, sub}\}$ that enter linearly in the number of facilities constructed in a given village. To capture the spatial nature of the problem, building in a village involves favoritism associated with both that village and the surrounding villages, down-weighting by distance.

$$D_v(X_v, X_{-v}) = \sum_{v' \in \mathcal{V}_{\text{in}}} W_{v'} X_{v'} \Big/ \sum_{v' \in \mathcal{V}_{\text{in}}} W_{v'}, \quad W_{v'} = (1 + \eta \cdot \text{distance}(v, v'))^{-2},$$

where I suppress X_{-v} in the objective function. I assume a single weighting function parameterized by η, but this function can in principle differ for each variable.

I further allow for unobservable choice factors. I consider a decomposition of village, time, and village-time factors, and I assume that these factors enter linearly as the observables do.

$$\xi(a^t) = \sum_{v \in \mathcal{V}_{\text{in}}} \sum_f n_{fv}(a^t) \cdot D_v\Big(\lambda_{fv} + \psi_{ft} + \varepsilon_{fvt}\Big), \tag{8}$$

where $\mathbb{E}(\varepsilon_{fvt}) = 0$ by construction. In general, the unobservables reflect underlying heterogeneity in preferences over villages. They absorb unobserved sources of favoritism, but they also arise from mismeasured consumer surplus. For example, demand shocks arising from disease outbreaks and misspecification of the demand system will both enter here. Unobservables also absorb variation in costs unaccounted for by a budget constraint based on the number of facilities. For example, high land and labor costs in one region make building a hospital there more expensive than building in another region. Accommodating unobservables is therefore critical in this setting where ignoring unobservables induces selection bias in estimation, and furthermore where the econometrician is unlikely to observe all choice factors underlying the observed placement decisions.

Finally, I set consumer surplus as the numeraire, such that preferences over other factors are denominated in dollar terms. I omit the fixed costs of each facility type without loss of generality because these costs are fixed across placement choices.

6.2 Additional assumptions for estimation

I assume a fixed relationship across parameters by facility type. Doing so avoids the need to estimate the full set of parameters separately for each facility type.

$$\theta_{\text{hosp}} = \theta\,, \quad \theta_{\text{clin}} = \gamma_{\text{clin}} \cdot \theta_{\text{hosp}}\,, \quad \theta_{\text{sub}} = \gamma_{\text{sub}} \cdot \theta_{\text{hosp}}\,,$$

for $\theta \in \{\tau^P, \tau^G, \tau^E, \{\lambda_v\}\}$. I also set the annual discount factor to $\beta = 0.95$, as it is generically unidentified (Magnac and Thesmar 2002).

I further assume that the government has perfect foresight over population growth, which evolves exogenously. Given future populations, the government can evaluate the consumer surplus generated over time by any given placement decision. I do not need to make assumptions on the government's expectations over time unobservables ψ_{ft} or village-time unobservables ε_{fvt}. Furthermore, new facilities in Indonesia are allocated using population-based rules, and so exogenous population growth implies that facility budgets also evolve exogenously over time. Otherwise, if budget allocations tomorrow depended on placement choices today, then the payoff associated with a given placement would need to account for these future budget effects above and beyond the objective function described above.

I also make several assumptions for computational feasibility. I assume that the government is unable to reallocate its budget across periods. It therefore spends the entirety of its budget in each period, simplifying the choice space by restricting it to the number of facilities observed in the data in each period.

$$\mathcal{A} = \left\{ b \;\middle|\; \sum_{v \in \mathcal{V}_{\text{in}}} n_{fv}(b^t) = \sum_{v \in \mathcal{V}_{\text{in}}} n_{fv}(a^t),\ \forall\, f, t \right\}. \tag{9}$$

Next, I assume homogeneity in facility age and focus instead on the number of facilities of each type in each village. Finally, I assume away strategic responses placement decisions. In reality, the private sector may respond to the placement of public facilities, although private hospitals serve a different market than public hospitals do (i.e., the very wealthy). Under decentralization, the responses of other districts may also be important.

6.3 Estimation

I estimate government preference parameters τ with the revealed-preference approach described in Pakes (2010) and Pakes et al. (2015). Let a denote the actual placement policy observed in the data. For true preference parameters τ^0,

$$\pi(a;\, \tau, \omega^0) \geq \pi(b;\, \tau, \omega^0) \quad \forall\, b \in \mathcal{A} \tag{10}$$

for alternative policies b given demand parameters ω^0. That is, at the true parameter values, the chosen option at least weakly dominates all other options. I operationalize this insight by choosing a set of alternatives b, constructing the associated revealed-preference inequality for each alternative, and ruling out candidate values of parameters τ that violate one or more of these inequalities. This approach achieves dimension reduction by evaluating only a subset of the possible alternatives. By contrast, a nested fixed-point approach picks a candidate value for parameter τ and evaluates every policy to find the optimal policy given τ; it then chooses the value of τ that produces the predicted optimal policy most similar to the observed policy. The latter approach is infeasible in this context given the computational complexity of computing the optimal policy.

Expanding inequality 10 to show the difference in payoffs between actual policy a and alternative policy b, the revealed-preference inequality becomes

$$\sum_{t=1}^{\infty} \beta^{t-1} \Big(\Delta SX(a^t, b^t;\, \tau) + \Delta\xi(a^t, b^t;\, \lambda, \psi, \varepsilon) \Big) \geq 0\,, \tag{11}$$

where I suppress the demand parameters ω^0, and I define

$$\Delta SX(a^t, b^t;\, \tau) \equiv S(a^t;\, \tau) - S(b^t;\, \tau) + X(a^t;\, \tau) - X(b^t;\, \tau)\,.$$

The challenge is in constructing a sample analogue to inequality 11 given (1) dynamics and (2) unobservables. To address these issues, I use techniques described in applications Holmes (2011) and Ho and Pakes (2014). For simplicity, in discussing identification I assume only one facility type and suppress all f subscripts. Estimation uses information from all facilities types – hospitals, clinics, and subclinics – jointly, and the extension is straightforward.

The first challenge arises in capturing the dynamic effects of a given policy. A new facility in period t impacts payoffs both in period t and in all future periods, but calculating future payoffs requires knowing future placements. For example, placing a facility in village v may have large benefits today, but these marginal benefits will decrease if the neighboring village is slated to receive a facility tomorrow. One approach is to solve within a limited lookahead window as in Zheng (2016), but this approach sacrifices the last periods of the panel data and only captures dynamics within the lookahead window.

Instead, I sidestep these issues with "pairwise resequencing" as in Holmes (2011). I select alternatives that swap the construction order of two facilities in the actual policy. For example, for actual policy $a = (v_1, \{v_2, v_3\}, v_4, \ldots)$, a pairwise resequenced alternative is $b = (v_2, \{v_1, v_3\}, v_4, \ldots)$. After the second period, these policies result in the same number of facilities in every village. Formally, the set $\mathcal{S} \subset \mathcal{A}$ of "swapped" alternatives to actual policy a are such that

$$n_v(a^t) - n_v(b^t) = \begin{cases} 0 & \text{for } t \notin s(b),\ v \in \mathcal{V} \\ -1 & \text{for } t \in s(b),\ v = w_1(b) \\ 1 & \text{for } t \in s(b),\ v = w_2(b) \\ 0 & \text{for } t \in s(b),\ v \in \mathcal{V} \setminus \{w_1(b), w_2(b)\} \end{cases} \tag{12}$$

where $s(b) = \{s_1(b), s_1(b)+1, \ldots, s_2(b)-1\}$, $s_1(b)$ is the earlier period involved in the swap, $s_2(b)$ is the later period, $w_1(b)$ is the village that receives its facility earlier in the swap, and $w_2(b)$ is the village that receives it later.[6] For swapped alternatives $b \in \mathcal{S}$, applying the first line of condition 12 to inequality 11 gives

$$\sum_{t=s_1(b)}^{s_2(b)-1} \beta^{t-1} \Big(\Delta SX(a^t, b^t; \tau) + \Delta\xi(a^t, b^t; \lambda, \psi, \varepsilon) \Big) \geq 0\,, \tag{13}$$

since $n_v(a^t) = n_v(b^t)$ for all villages v outside of the swap-relevant periods. That is, the per-period payoffs of actual policy a and swapped alternative b are identical in

[6] If facilities are constructed at the beginning of the period, then in period s_2 both of the facilities involved in the swap have been built. As such, the equality holds in period s_2. If facilities are instead constructed at the end of the period, then the equality holds at all $t \notin \{s_1(b) - 1, s_1(b), \ldots, s_2(b)\}$.

the periods before and after the swap, thereby eliminating dynamics beyond period $s_2(b)$. Figure A5, appended, presents the intuition visually.

The second challenge lies in the unobservable terms of inequality 13. Ignoring these terms leads to selection bias: given that policy a was chosen, the unobserved payoff of a likely exceeds that of unchosen policy b. To proceed, I apply the assumed functional form on the unobservables as described in equation 8.

$$\Delta\xi(a^t, b^t;\, \lambda, \psi, \varepsilon) = \sum_{v \in \mathcal{V}_{\text{in}}} \big(n_v(a^t) - n_v(b^t)\big) \cdot D_v\Big(\lambda_v + \psi_t + \varepsilon_{vt}\Big). \tag{14}$$

Substituting this expression, applying the rest of condition 12, and applying the budget-spending assumption of equation 9, inequality 13 simplifies to

$$\sum_{t=s_1(b)}^{s_2(b)-1} \beta^{t-1}\Big(\Delta SX(a^t, b^t;\, \tau) + \Delta D(\lambda) + \Delta D(\varepsilon_t)\Big) \geq 0\,, \tag{15}$$

where I define

$$\Delta D(X) \equiv D_{w_2(b)}\big(X_{w_2(b)}, X_{-w_2(b)}\big) - D_{w_1(b)}\big(X_{w_1(b)}, X_{-w_1(b)}\big)\,.$$

I address the $\Delta D(\lambda)$ terms by estimating the village fixed effects λ_v directly, and the $\Delta D(\varepsilon_t)$ terms with an aggregation step. Time effects ψ_t cancel because the number of facilities is held constant.

I estimate the model separately on the pre- and post-reform data. As such, the parameter values – including the village fixed effects – are allowed to differ across the two periods. Thus, I estimate parameters $\tau \equiv \{\tau^S, \tau^P, \tau^G, \tau^E, \{\lambda_v\}, \eta, \gamma_{\text{clin}}, \gamma_{\text{sub}}\}$. First, I identify K valid swaps and form the left-hand side of inequality 15 for each. The computationally intensive part of the estimation procedure is in calculating these inequality values for all K swaps, although the process is readily parallelizable.

$$I_k(\tau) = \sum_{t=s_1(b)}^{s_2(b)-1} \beta^{t-1}\Big(\Delta SX(a^t, b^t;\, \tau) + \Delta D(\lambda)\Big) \tag{16}$$

This expression contains only predicted values, observed values, and parameters to be estimated. Second, I form aggregated moments by averaging these values in groups

$\mathcal{G}_{\text{g}+}$ and $\mathcal{G}_{\text{g}-}$ for $g \in \{\tau^S, \tau^P, \tau^G, \tau^E, \{\lambda_v\}\}$. That is, in order to identify upper and lower bounds for each parameter of interest, I group swap values based on whether the swap increases or decreases the variables associated with the parameter.[7]

$$M_g(\tau) = \sum_{k=1}^{K} \Big(\mathbb{1}(k \in \mathcal{G}_g) \cdot I_k(\tau) \Big) \Big/ \sum_{k=1}^{K} \Big(\mathbb{1}(k \in \mathcal{G}_g) \Big) \tag{17}$$

Since village-time shocks are mean-zero by construction, these moments coincide with the aggregated revealed-preference inequalities implied by the model.[8] Third, by revealed preference $M_g(\tau) \geq 0$ for all groups g at the true preference parameters τ^0. I therefore choose parameters τ that minimize violations of the moment inequalities.

$$\widehat{\tau} = \arg\min_{\tau} \left\{ \frac{1}{G} \sum_{g=1}^{G} \big(\min\{M_g(\tau), 0\} \big)^2 \right\} \tag{18}$$

Because the moments can be formed offline, at this point the optimization problem is computationally light.

6.4 Estimates

Table 3 shows how many valid swaps can be identified based on the policy a observed in the data. Swaps are constrained to be within districts both before and after the reforms.[9] I omit swaps that span redistricted borders. Table 4 shows

7 Grouping inequalities with different types of identifying variation may eliminate it. For example, combining an inequality with an alternative that increases costs and one with an alternative that decreases them will eliminate the identifying variation.

8 Since $\mathbb{E}(\varepsilon_{vt}) = 0$, the unobserved ε_{vt} terms can be averaged out. The selection issue is that these shocks, which are unconditionally mean-zero, may not be mean-zero after conditioning on the chosen policy a. In this case, however, the assumed linearity of the unobservable component terms delivers an inequality that is additive in the λ_v and ε_{vt} terms no matter the chosen policy a. That is, regardless of where policy a places facilities, the alternative policy involving swap villages $w_1(b)$ and $w_2(b)$ yields an inequality containing the same $\varepsilon_{w_2(b),t}$ and $\varepsilon_{w_1(b),t}$ terms. Thus, the inequality need not condition on chosen policy $\mathring{a}$, and the unconditional average is sufficient for addressing the ε_{vt} terms.

9 Swaps compare the actual policy a to some alternative policy b within the decision-maker's choice set. If alternative b is not within the decision-maker's consideration set, then the resulting revealed-preference inequality will not necessarily hold. After decentralization, district governments choose facility placement within their districts. Before decentralization, in principle the central government chooses over the full set of villages. The full set of swaps is therefore very large. In practice, however, population-based rules govern the allocation of facilities to districts, so placement choices may still be constrained to be within districts. As such, I consider only the

Table 3: Number of potential swaps for estimation

	Data	Swaps		
	PODES	Hospitals	Clinics	Subclinics
Pre-reform	1990, 93, 96, 2000	1,089	39,522	420,755
Post-reform	2003, 06, 08, 11, 14	5,013	45,267	299,056

Swaps are pairs of facility allocations – one observed in the data and one hypothetical – in which the placement order for two facilities has been swapped. In other words, a swapped allocation is a pairwise resequencing of an observed allocation. Swaps are all within districts and are restricted to be either within the pre-reform period or within the post-reform period. I form swaps separately for each facility type. The table shows the total number of swaps available, but where the total is large I sample of subset of swaps for use in estimation.

estimates of government preference parameters τ. Estimation yields point estimates, which occur when not all inequalities can be simultaneously satisfied. Indeed, point identification is common in cases with a large number of moments.

District governments are only somewhat less likely to internalize spillovers increases in the post-reform period. Patronage and *Golkar* support play a larger role in the pre-reform period, while ethnicity does not play a major role in either period. Figure A7, appended, maps the estimated village preferences λ_v for Jakarta in the post-decentralization period. The majority of villages have a large, negative values of λ_v, which reflects that they do not receive many facilities despite potentially large welfare benefits.

I examine the goodness of fit of the model by evaluating the set of inequality values given by equation 16 at the estimated parameters, and I report the percentage that are positive as an "R-squared" in table 4. The percentage that are positive reflects the degree to which the model and the estimated parameters explain the observed placement, at least relative to its one-step deviations.

6.5 Discussion

I assume village populations are fixed in calculating counterfactual consumer surplus under alternative placements. Estimates will be biased if village populations respond endogenously to changes in infrastructure. In particular, surplus gains to

subset of swaps that occur within districts.

Table 4: Government preference parameter estimates

	Pre-reform	Post-reform
Internalized spillovers (τ^S)	0.79	0.66
Patronage (τ^P)	3.41	0.85
Golkar (τ^G)	2.85	1.03
Ethnicity (τ^E)	0.04	0.07
"R-squared"	0.64	0.70

Each row in the upper panel corresponds to an estimated parameter of the government objective function. Internalized spillovers indicates the extent to which a district government values spillover benefits to non-constituents. A value of one represents full internalization and is what the social planner would do. Patronage refers to villages within the Suharto patronage network, as proxied by military presence. *Golkar* is whether a village is an historical supporter of Suharto's political party, as proxied by vote shares in Suharto-era elections. The R-squared shown in the bottom panel indicates the proportion of revealed-preference inequalities that can be satisfied under the estimated parameters.

alternative placements will be understated: with migration, some of the people in villages that lose facilities will move to villages that gain facilities, tempering the surplus loss for these people (and therefore increasing the surplus gains). A countervailing force is increased congestion in the villages that gain facilities, although the demand estimates suggest that this effect will be smaller in magnitude. Accommodating this force requires a separate model of individuals' location choices, as I adopt in related work on schooling infrastructure in Indonesia (Hsiao 2020). Combining both models would require capturing the strategic game between individuals and governments.

Another implicit assumption is that the government makes decisions over healthcare infrastructure independently of other infrastructure. Estimates will be biased if decisions are made jointly across all types of infrastructure, although in practice these decisions are made within individual government departments. Village fixed effects absorb part of this non-health infrastructure, and I can use the PODES data to control directly for a range of observed infrastructure, including schools and roads.

I also require that unobserved village preferences λ_v be fixed over time within the pre- and post-reform periods. The tension is that district mayors may change in either the pre- or post-periods, and as such their preferences may differ. One way forward is to place some parametric structure on the λ_v terms, for example based on political party, hometown, or some other observed mayor characteristics. Another approach is to test robustness by estimating the model separately on districts in which mayors do and do not change.

Finally, I note that village preference λ_v subsume a variety of structural objects that make interpreting these terms difficult. While they may contain true unobserved motivations for deviating from the surplus-maximizing allocation, they may also contain misspecification error and unobserved costs. I estimate these terms as nuisance parameters in order to obtain unbiased estimates for other parameters, but their catch-all nature means that they may not be indicative of misallocation themselves. Instead, I turn to observables like patronage, ethnicity, and constituent status to understand the sources of misallocation in this setting.

7 Supporting Evidence

Using quasi-experimental variation in electoral accountability and spillover effects, I provide reduced-form evidence in support of my findings. I control for facilities constructed, initial stocks of facilities, populations, and island group dummies.

For electoral accountability, I compare districts with differential exposure to the Suharto-appointment mayors, who were arguably less constrained by electoral concerns. Martinez-Bravo et al. (2017) establishes that this variation is quasi-random both because the end of the Suharto regime was unexpected and because the variation in district term dates is a vestige of Dutch colonial rule. I compare districts with more and less exposure to a Suharto mayor, and I study how this effect varies over time with the specification

$$\text{misallocation}_{dt} = \beta^e \left(\sum_t \text{end\_date}_{dt} \cdot \delta_t \right) + x_{dt}\beta + \delta_t + \varepsilon_{dt} \,. \tag{19}$$

The treatment variable end_date_{dt} captures exposure: districts with later term expiration dates for Suharto-appointed mayors are districts with greater exposure.

For spillover effects, I study the effect of redistricting on misallocation in an event-study framework. Burgess et al. (2012) and Bazzi and Gudgeon (2017) argue that the timing of redistricting is plausibly exogeneous around two national moratoria placed on redistricting from 2004 to 2006 and from 2009 to 2012. Approximately 32% of the

Figure 4: Effects of Suharto mayors and redistricting on misallocation

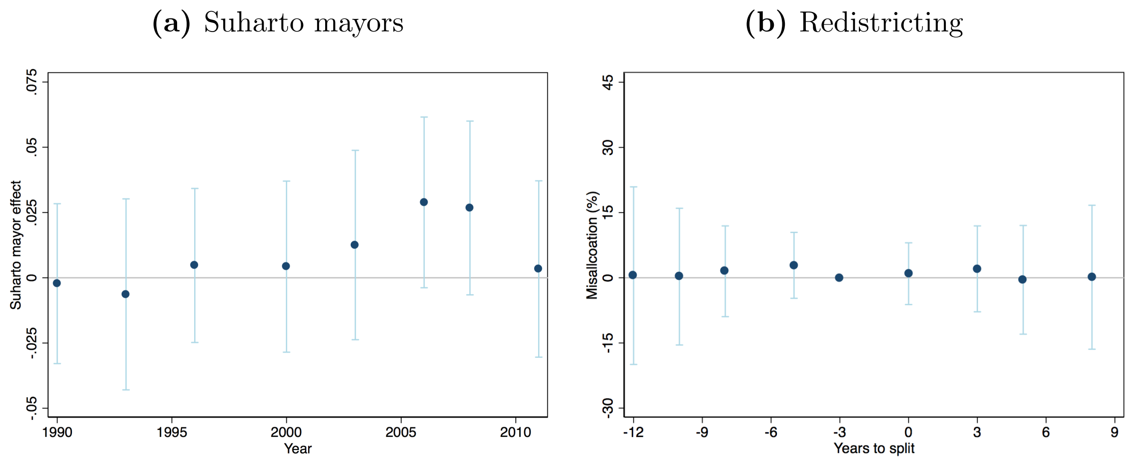


Figure 4a shows the difference in facility misallocation between districts in which Suharto mayors remained in power after the fall of Suharto and districts in which they did not. Before 2000, Suharto was in power and therefore all districts were headed by Suharto mayors. Figure 4b shows the impact of redistricting on misallocation as an event study. Redistricting splits a parent district into child districts and therefore increases the potential for uninternalized spillovers as a single constituency becomes multiple constituencies.

districts in my sample undergo redistricting. Restricting attention to these districts, the following specification compares misallocation before and after redistricting.

$$\text{misallocation}_{dt} = \beta^r \text{redistricted}_{dt} + x_{dt}\beta + \delta_d + \delta_t + \varepsilon_{dt} \tag{20}$$

The treatment variable redistricted_{vt} takes a value of zero before the first instance of redistricting for a given district and a value of one afterwards.

Figure 4 presents the impact of these channels. Exposure to Suharto mayors has no effect in the pre-reform period, and this balance in the pre-treatment period is consistent with the treatment being as if randomly assigned. In the post-reform period, the effect is positive and significant. That is, greater exposure to these mayors that were unconstrained by electoral accountability corresponds to greater misallocation in healthcare facility placements. For redistricting, I find no evidence that uninternalized spillovers generated significant misallocation in terms of social welfare. Taken together, the benefits of electoral accountability seem to outweigh the costs of uninternalized spillovers in the post-reform period. These district-level findings are consistent with the structural findings, which provide further texture by taking advantage of variation at the village level.

8 Conclusion

Infrastructure investment is central to economic development, but it is also a major target of corruption. This paper asks whether electoral accountability helped limit corruption in Indonesia's national expansion of healthcare infrastructure – one of the largest such efforts in recent history. I draw on spatial panel data on healthcare facility access and usage to study the construction of new hospitals, clinics, and subclinics in Indonesia, both before and after democratization in 1999. I quantify the consumer surplus generated by new facilities with a spatial model of demand for healthcare. Particularly prior to democratization, I find that the actual allocation of new facilities falls far short of the optimal allocation. To understand why, I model the facility placement decision as a dynamic discrete choice problem, and I estimate the government's objective function by revealed preference.

My main finding is that democratization decreases misallocation overall. My structural estimates suggest that, after democratization, there is less bias toward Suharto-era villages, such as those within the patronage network. A countervailing force is that spillover effects were less internalized as local electoral accountability pushed local governments to prioritize constituents over non-constituents. However, the magnitude of this second effect is relatively small. Using district-level variation in electoral accountability and district boundaries, I also find reduced-form evidence in support of this narrative.

I leave several directions open for future work. First, public and private healthcare facilities may interact in ways that I do not currently accommodate. Private facilities may compete in prices or compete spatially with public facilities, and as such may respond endogenously to changes in the placement of public infrastructure. Second, I focus on healthcare infrastructure, but healthcare may interact with other investments, such as in education or roads. Future work could study investment across several types of infrastructure jointly. Third, path dependence arises in spatial settings when infrastructure is durable because the marginal effect of new investment depends on the placement of prior investment. Thus, whether they be from corruption or otherwise, distortions today limit the gains from investment in later periods, and future work might focus on these cumulative effects.

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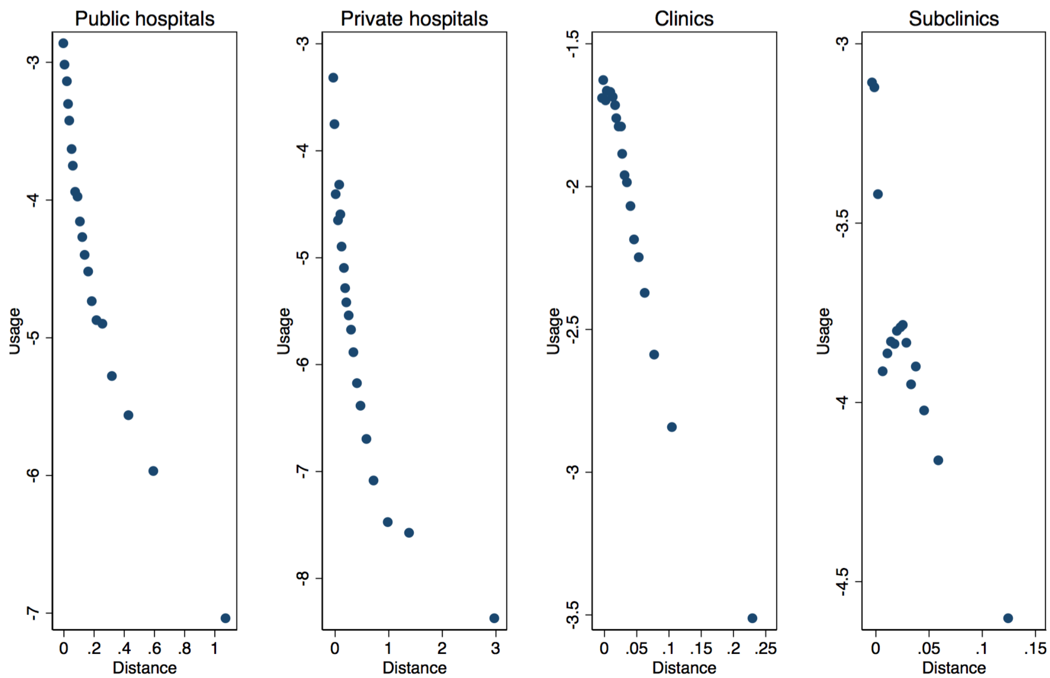
Appendix

Figure A1: Correlation between usage and distance by facility type



Binned scatter plots controlling for year fixed effects.

Figure A2: Pretrends for usage before public hospital construction

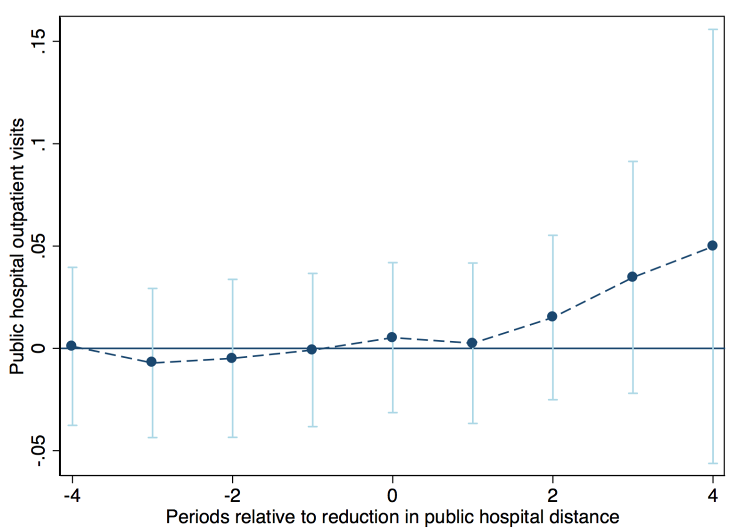
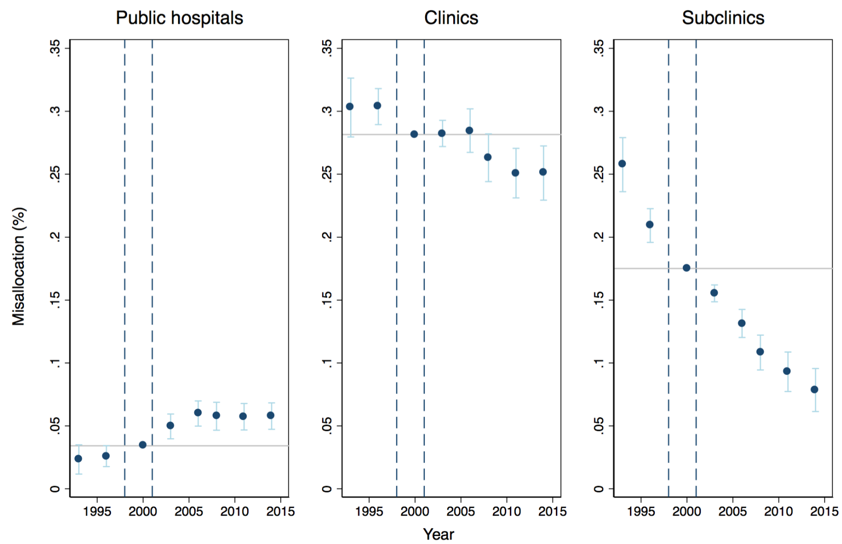
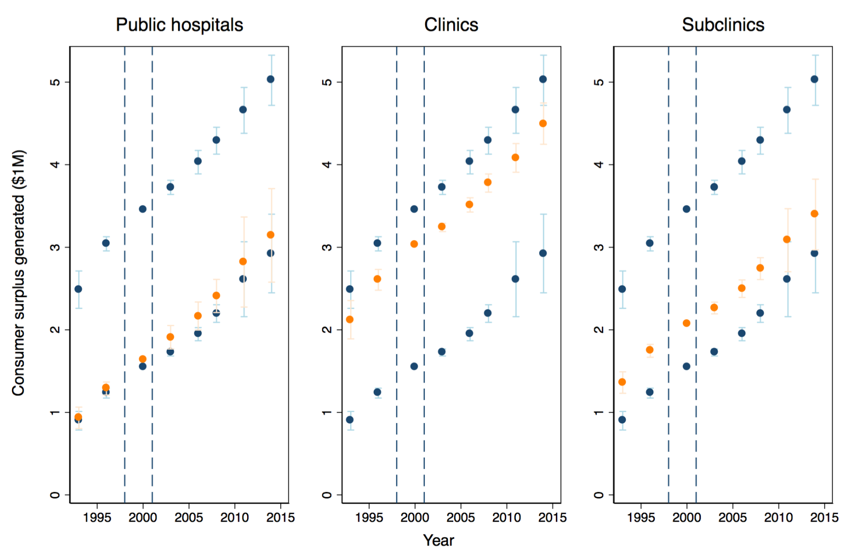


Figure A3: Misallocation over time by facility type



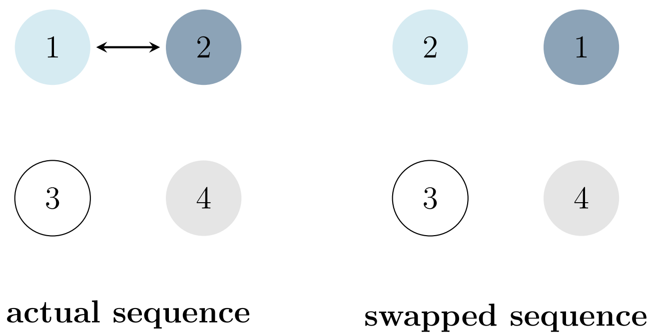
Misallocation is defined as one minus the proportion of the best achievable consumer surplus gain that is achieved by the observed placement. It is zero when the actual placement coincides with the surplus-maximizing placement. These figures the contribution of each facility type of overall misallocation. For each, I compute the optimal placement of the facility type of interest holding fixed all other facility types.

Figure A4: Best achievable vs. actual policy over time by facility type



The top blue line is the maximum consumer surplus gain achievable with the facility budget in a given time period. The bottom blue line is the consumer surplus gain achieved by the actual placement. The orange line is the maximum achievable by optimizing over the facility type of interest while holding all other facility types fixed. For each period, the benchmark placement $\underline{a}$ is the facility placement in 1990.

Figure A5: Pairwise resequencing eliminates dynamics outside of swap



Suppose the observed order of construction is red, blue, white, and gray. I consider an alternative that swaps the order of red and blue construction. These two sequences result in the same allocation from the second period, so attention can be restricted only to where there are differences – namely, periods within the swap (in this case, the first period). In this way, choosing alternatives by pairwise resequencing eliminates dynamic considerations outside of the swap periods.

Figure A6: Spurious misallocation under misspecification of the dynamic horizon

Each circle is a village that is a candidate to receive a facility. On the left, without accounting for future construction, there is only one facility to be placed in the current period. Placing it in the middle village puts it in close proximity to all villages. On the right, the decision maker accounts for having an additional facility to place in the following period. It is therefore optimal to place the first facility in the left village given that the second facility will be placed in the right village. This simple example illustrates the importance of how the dynamic horizon – the look-ahead window – is specified. A forward-looking decision-maker will place the first facility in the left village, but this action looks like misallocation under a model that assumes a myopic decision-maker.

Figure A7: Estimated village preferences λ_v, Jakarta post-decentralization

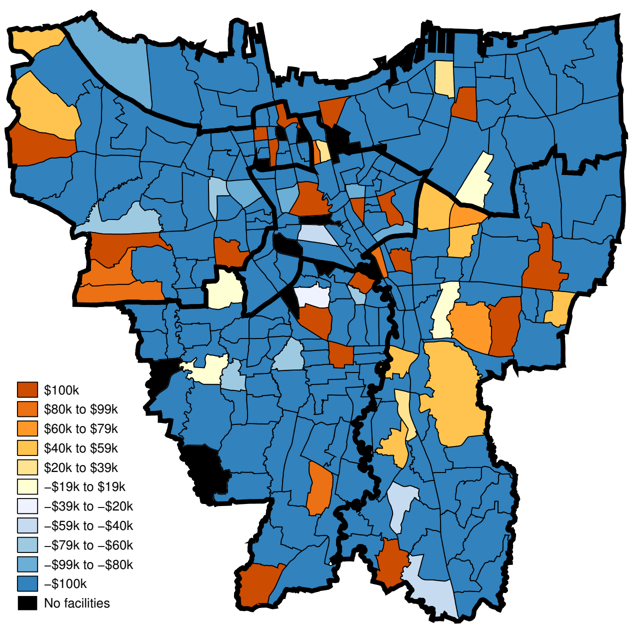


Table A1: Usage by facility distance and congestion, population-density interaction

	Estimate	Standard Error
Distance, public hospital	-2.058***	(0.0568)
Distance, private hospital	-0.950***	(0.0298)
Distance, clinic	-2.817***	(0.241)
Distance, subclinic	-4.467***	(0.447)
Distance, public hospital × population density	-0.0424	(0.0353)
Distance, private hospital × population density	-0.0303	(0.0210)
Distance, clinic × population density	-0.155	(0.137)
Distance, subclinic × population density	-0.803	(0.646)
Congestion, public hospital	-0.0206***	(0.00298)
Congestion, private hospital	-0.0133***	(0.00123)
Congestion, clinic	-0.281***	(0.0346)
Congestion, subclinic	-0.468***	(0.0380)
Congestion, public hospital × population density	0.00268	(0.00171)
Congestion, private hospital × population density	0.00196**	(0.000900)
Congestion, clinic × population density	0.0172**	(0.00738)
Congestion, subclinic × population density	0.0426***	(0.0136)
Price	-0.764***	(0.152)
Village FE	x	
Facility type-year FE	x	
Observations	202,668	

Each column is a single conditional multinomial logit regression with village and facility type-year fixed effects. The unit of observation is a village-year-facility type, where the set of facility types represents a village's choice set in a given year. The outcome is usage by facility type, as recorded in the SUSENAS data. Distance is to the closest facility of each type and is measured in units of 100 km. Congestion of the closest facility is the number of people for whom this facility is the closest of its type. This variable is measured in units of 100,000 people. Price is measured in units of \$100 (in year 2000 USD). Population density is measured in units of 10,000 people per square kilometer. Additional controls include population and ruralness. Standard errors are clustered by village. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.