Competing Complements in Public-Private Hospital Markets

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17 October 2025

Abstract

Whether public firms crowd out or crowd in private entry depends on whether competitive effects or complementarities dominate. I show this tension in the Malaysian hospital market where public and private hospitals coexist. I exploit the staggered construction of public hospitals between 1996 and 2013 to identify causal effects on private hospital entry. I find that public hospitals crowd in private entry in aggregate, but this varies by hospital type. Specialist hospitals crowd in private entry through labor spillovers that outweigh competition, while non-specialist hospitals crowd out entry as competitive effects dominate. A dynamic entry model estimates that a new specialist public hospital reduces private entry costs by 19 percent but captures 55 percent of market share post-entry. These findings demonstrate that effective public provision design requires understanding whether public provision complements or substitutes for private investment.

*I thank the Malaysia Health Systems Research project, led by the Ministry of Health Malaysia and Harvard T.H. Chan School of Public Health for access to multiple datasets. All errors are mine.

1 Introduction

Governments face a tension when expanding public provision in markets like health care, education, water, and transportation. On one hand, increased public provision may crowd out private investment through substitution effects (Cutler and Gruber, 1996; Lo Sasso and Buchmueller, 2004; Gruber and Simon, 2008; Dinerstein and Smith, 2021a). On the other hand, public provision can generate complementarities that crowd-in private investment by stimulating demand, providing infrastructure or supply-side complementarities (Duggan and Scott Morton, 2006; Glaeser and Gottlieb, 2008; Kline and Moretti, 2014; Mitrunen, 2024). These opposing effects suggest that the impact of public provision on private investment depends on the magnitude of complementarities relative to competitive effects.

Understanding this tension is particularly important in hospital markets globally, where public and private hospitals increasingly coexist (WHO, 2020). Most developed countries rely on mixed hospital systems, with public facilities handling emergency care and serving disadvantaged populations while private hospitals focus on elective procedures and affluent patients. In developing countries, private providers often deliver the majority of healthcare services, while relying on public hospitals for training, referrals, and unprofitable services[1]. Given the scale of hospital investments and their impact on healthcare access, understanding the interactions between public and private hospital provision has important policy implications.

Despite the sheer scale of public hospital investments worldwide[2], there is limited empirical evidence on how public hospital construction affects private hospital entry. Public hospital investment decisions often do not account for private sector responses, yet these investments could either crowd in or crowd out future private investors. Crowd out occurs through direct patient competition. Public hospitals tend to be subsidized, capturing a significant share of patients and reducing private revenues and deterring new entrants. However, public hospitals also serve as training sites for physicians and other healthcare professionals, who complete compulsory residencies in public facilities before practicing independently. When public hospitals expand training programs, they increase the local supply of qualified professionals available for private practice, reducing recruitment costs and barriers to private hospital entry. The net effect thus depends on whether these positive labor externalities outweigh negative demand substitution.

[1] The US relies primarily on private hospitals with public provision concentrated in veterans' affairs and safety-net hospitals. European countries like Germany and France maintain mixed systems with both public and private hospitals competing under regulated insurance frameworks. The UK's National Health Service (NHS) mostly consist of public hospitals but have recently encouraged the growth of private sector involvement amidst fiscal constraints. Developing countries such as India, Brazil, and Indonesia feature large private hospital sectors alongside public systems focused on basic care and emergency services. China and other transition economies have shifted from entirely public systems toward mixed provision allowing private entry.

[2] Across OECD countries, hospital-delivered activities account for about 39 percent of health system funding (OECD, 2023).

Given the effects on the private sector, public hospital allocation decisions create important efficiency trade-offs. Private hospitals typically enter areas with high willingness-to-pay, while public hospitals prioritize equity and serve areas of greatest need. When public hospitals expand into high willingness-to-pay areas that would attract private investment, they may inadvertently crowd out private entry that could have occurred, while forgoing opportunities to build public capacity in underserved areas where private hospitals would not enter. Understanding these responses is therefore important for optimizing the allocation of public healthcare investments and maximizing total healthcare capacity.

In this paper, I study the effects of new public hospitals on private hospital entry in Malaysia. The Malaysian hospital market exhibits several traits that are similar to many other countries that rely on both the public and private sector. Private hospitals cluster in urban areas and serve higher-income populations, while public hospitals are more evenly distributed to ensure geographic access. Private hospitals operate at smaller scale but charge significantly higher prices relative to subsidized public hospital services. Public hospitals serve a dual function as both healthcare providers and essential training centers for physicians through mandatory residency programs, creating potential labor market spillovers, while simultaneously providing heavily subsidized care that directly competes with private providers for patients.

These institutional features suggest that public hospitals can affect private hospital entry through two opposing channels. On one hand, public hospitals may crowd out private entry by capturing market share through subsidized pricing and expanded service capacity. On the other hand, public hospitals may crowd in private entry by expanding the local supply of trained physicians, thereby reducing private hospitals' operational costs of hiring medical staff. The net effect on private entrants thus depends on the relative magnitude of these competition and complementarity mechanisms.

A central challenge in studying hospital markets in developing countries is data availability. I address this by constructing two datasets from a combination of administrative data, survey data and primary data collection. First, for the reduced form analysis, I build a district-year panel that links administrative records on the timing and type of public hospital openings and capacity upgrades, to private hospital entry counts and facility characteristics, and census-based demographics and physician stocks. Second, for the structural model, I compile a hospital level shares dataset to estimate demand and entry. This includes electronic health records on admissions with a focus on vaginal deliveries, a geocoded household survey to recover patient choice sets, distances, and outside options, and primary collection of private 'maternity package' prices.

To identify the causal effects of public hospital entry on private investment, I exploit the staggered timing of public hospital construction across districts between 1996 and 2013. During this period, Malaysia built 25 new public hospitals in response to political backlash from proposed healthcare privatization policies. This public expansion occurred simultaneously with the growth of the private hospital industry, leading to multiple districts with public-private hospitals.

Public and private hospitals face different location incentives that drive their entry decisions, which is important for identifying causal effects since public hospital placement is not determined by the same factors that attract private investment. Private hospitals enter districts with favorable market conditions. This includes higher population growth, greater shares of college-educated residents, and existing specialist physician labor pools. In contrast, public hospitals prioritize underserved areas, particularly districts lacking existing public hospitals. Malaysia's centralized five-year development planning process guides public hospital allocation, with the Ministry of Health and regional authorities identifying locations based on population needs, facility capacity constraints, and accessibility gaps.

My analysis compares the 25 districts that received new public hospitals during this period to 22 districts that remained untreated by 2013. The never-treated districts serve as controls under the assumption that they will eventually receive public hospitals through Malaysia's ongoing development planning process. The key identification assumption is that the timing of public hospital allocation is exogenous to private hospital entry trends. While treatment and control districts are balanced on demographics such as ethnicity, education, and availability of existing healthcare infrastructure, some differences exist in population size and rurality, showing that this is not a perfectly randomized setting.

To test whether public hospital construction correlates with unobserved determinants of private entry, I conduct balancing regressions that predict private hospital counts using observable district characteristics and examine whether these predicted values correlate with public hospital construction. The results show small and statistically insignificant correlations, suggesting the event study design adequately controls for observable confounders. I add several robustness checks including synthetic difference-in-differences estimation, coarsened exact matching on key characteristics, and alternative control group specifications. I estimate dynamic treatment effects using the Sun and Abraham (2021a) estimator to account for heterogeneous treatment effects across cohorts in this staggered adoption design.

The results show a surprising effect of public hospitals on private entrants. On average, the construction of a new public hospital increases private hospital entry by 47 percent (0.465 hospitals per district relative to the pre-treatment mean of 0.979 private hospitals). This crowd-in effect emerges immediately after public hospital construction and persists throughout the post-treatment period. However, this average effect masks substantial heterogeneity by hospital type that provides hints on the underlying mechanisms. Specialist public hospitals that are staffed by specialty-specific physicians who provide advanced medical training crowd in private hospitals by 61.5 percent. In contrast, non-specialist public hospitals staffed primarily by general practitioners and nurses crowd out private entry by 56 percent. These opposing effects show that the type of public hospital investment is an important caveat for whether public provision complements or competes with private investment.

This finding aligns with a conceptual framework where labor market complementarities can exceed competitive effects when public hospitals generate sufficient physician training spillovers. Specialist public hospitals serve as training centers that expand the local supply of specialist physicians, reducing private hospitals' operational costs of hiring qualified medical staff. Non-specialist hospitals, while still competing for patients through subsidized care, do not generate the same physician training benefits that would offset competitive pressures.

To directly observe the mechanisms driving these results, I estimate a 2x2 two-way fixed effects model on private hospital admissions and private specialist physicians. I use this approach rather than an event study given that I only observe private hospital admissions for 1996, 2006 and 2011, and private specialist physicians for years 1970, 1980 and 1991. The results show that public hospitals have large negative effects on private demand. Public hospitals reduce private hospital admissions by 66.6 percent. Specialist hospitals show somewhat smaller demand reductions of 46.7 percent.

For private specialist physicians, I use census data from 1970, 1980 and 1991 to identify self-employed physicians. I use this category to proxy for specialist physicians as specialist physicians tend to be employed on a contractual, non-wage basis by private hospitals[3]. I omit the census year 2000, as the employment classification ISCO coding system changed and self-employed physicians are no longer separately identified. Despite reducing private hospital demand, public hospitals increase the district's self-employed physician pool by 63.8 percent. The effect is particularly strong for specialist public hospitals, which increase private physicians by 75.9 percent. These results suggest that specialist public hospitals generate positive spillovers by training specialist physicians who subsequently enter private practice, while both hospital types exert competitive pressures on private hospital demand.

Next, to provide additional evidence on the competition effects, I use an alternative treatment of hospital upgrades. Upgrades increase the competitive capacity of public hospitals relative to the private sector without expanding specialist physician training or other complementary spillovers. Between 2003 and 2013, I identified 35 hospitals that received bed capacity upgrades. I estimate their effects on private hospital entry using never-treated districts as controls. The effects of upgrades are imprecisely estimated across all hospital types, making it difficult to draw strong conclusions about the mechanisms from this analysis. However, the general pattern that upgrade effects appear smaller

[3]Public physicians are salaried workers, and are treated similarly to civil servants

and less precise than new construction effects provides some support for the training complementarity hypothesis.

Finally, I examine the spatial location choices of private hospitals within districts that receive new public hospitals to further isolate the competitive effects. This analysis helps distinguish between district-wide complementarities in physician training spillovers and local competition effects through co-location. Using a ring event study design that compares private entry within 5 km of new public hospitals to entry 5-15 km away, I find that private hospitals avoid locating near public facilities. Private entry decreases by 36.1 percent within 5 km of new public hospitals, with effects concentrated in the immediate vicinity. These spatial patterns provide additional evidence for the competitive effects. While specialist public hospitals generate district-wide complementarities that crowd in private entry overall, private hospitals still avoid direct geographic proximity to public facilities to minimize local competition for patients.

In addition, I estimate the event studies from the pre-1996 policy uncertainty period, when public hospitals were proposed to be corporatized and potentially operate similar to private competitors, with no new public hospital construction planned. During this 16-year period (1980-1996), I find uniform crowd-out effects regardless of public hospital type. While private hospital construction continued to grow nationally, private hospitals avoided locating near public hospitals built during this period. This occurred for both specialist and non-specialist public hospitals, suggesting that when public hospitals were expected to operate as direct competitors rather than complementary public services, the complementarity effects disappeared entirely.

To quantify the dollar reduction in private entry costs when a new specialist public hospital is built, I estimate a dynamic entry model where potential private entrants make entry decisions based on expected future profits across districts, after observing the government announcement to build future public hospitals across districts. Entry costs are recovered from the revealed preferences of where private entrants choose to locate and their expected profits in each district.

Expected profits are estimated from Bertrand pricing equilibrium conditions. Estimating a full hospital demand system is not feasible given Malaysia's lack of comprehensive historical inpatient admissions records across public and private hospitals. Instead, I focus on vaginal birth deliveries, which is the largest volume inpatient service in both sectors. Consumers choose between the set of public and private hospitals within their district, and face an outside option of traditional or home births. I estimate hospital demand using each hospital's share of vaginal deliveries, combined with primary data on maternity package prices collected from private hospitals in a random coefficients logit model (Berry et al., 1995; Conlon and Gortmaker, 2020, 2023).[4]

To address price endogeneity, I construct excluded differentiation instruments following Gandhi and Houde (2019), which exploit variation in hospital characteristics across non-rival and rival hospitals within markets. I combine revealed preference data on hospital choices with micro-moments from a national survey of prospective parents that includes GIS coordinates, allowing me to compute distance from each household to every hospital option in their district. The outside option share captures preferences for home or traditional births based on stated preferences in the survey. The demand estimates are intuitive. Higher-income consumers are more price-sensitive than low-income consumers who primarily use public services, private hospital consumers strongly dislike travel distance, and those with private insurance show clear preferences for private hospitals. To obtain an estimate of total hospital profits, I then scale these estimates using hospital-specific ratios of vaginal deliveries to total inpatient admissions.

Given the static private entry profits, I estimate the dynamic entry model using the two-step estimator in Bajari et al. (2007) (hereafter referred to as BBL). Expected profits from entering a district are computed as the static-Bertrand total private profits divided by the number of incumbent private hospitals plus one. This assumes entrants expect to share market profits equally with private incumbents. In districts with no private incumbents, I simulate the entrant's profit in a market served only by public hospitals to ensure that every forward simulation state has an expected profit. Firms are assumed to observe current doctor supply, population and number of incumbent private hospitals, and the announced public hospital schedule. Private entrants draw an idiosyncratic entry cost shock, and also do not have strategic interactions with other potential entrants.

The BBL estimator proceeds in two steps, the first step involves recovering the equilibrium entry policy of private entrants based on observed entry decisions across districts that vary in their local physician pool, population, land prices, and numbers of public and private hospitals. In the second step, I invert those choice probabilities, forward-simulate doctor and population transitions under the estimated policy to obtain each state's expected present value of future profits, and then estimate a linear entry cost function that is the sum of fixed sunk costs and operational costs. Sunk costs of obtaining the land are proxied by land prices and population growth, while the operational costs are the costs associated with hiring the initial group of specialist physicians. By assuming linearity in the entry cost function combined with the T1EV cost shocks, the second-step estimator is simplified to a linear regression of expected profits on the entry cost function parameters. For robustness checks due to endogeneity concerns, I estimate the entry cost function using lagged private

[4] Private hospitals in Malaysia offer standardized "maternity packages" for birth deliveries (see Figure C.3 for examples).

physician density from 1980 as an instrumental variable for private physicians. Overall, my approach is simplified significantly from the second-step inequalities estimator due to the linearity in costs, but also because private entrants only make entry decisions (as opposed to exit, investment capacity in the usual BBL setting).

I estimate the model under three specifications that vary how the total private profit pool responds to new private entry: profits remain constant, profits grow, or profits shrink. In the baseline estimates that total private profits do not grow, the mean entry cost per private hospital is MYR 18 million (USD 4.2 million). Using these estimates, I quantify how new specialist public hospitals affect private entry incentives. A new specialist public hospital increases the local physician pool by 188.5 physicians, reducing private operational entry costs by 44 percent through labor market spillovers. However, the observed data show that these same public hospitals capture an average of 46 percent of market share upon entry, creating direct patient competition. This illustrates how public hospitals function as ″competing complements″. Public hospitals lower private entry barriers by expanding the available physician workforce while competing for the same patient base post-entry

Related Literature. This paper contributes to the growing literature on crowd-in and crowd-out effects of public market participation across sectors including education (Epple and Romano, 1998; Hoxby, 2000; Dinerstein and Smith, 2021b), health insurance (Duggan and Scott Morton, 2006; Curto et al., 2019; Saltzman, 2023), and consumer goods (Jiménez Hernández and Seira, 2022). My finding that public hospitals crowd in private hospitals contrasts with classic crowd-out results in health insurance, where Medicare expansions reduce private coverage (Cutler and Gruber, 1996; Gruber and Simon, 2008). Instead, my findings align with recent evidence of crowd-in effects: Andrabi et al. (2024) show that expanding public education increases private school quality through competitive pressure, while Atal et al. (2024) demonstrate that public pharmacy entry creates market segmentation that can benefit some consumers. My contribution is identifying labor market spillovers as a distinct mechanism for crowd-in effects, showing how public investment can simultaneously compete with and complement private firms depending on the magnitude of input complementarities.

My empirical findings also add to the literature on mixed public-private competition, which examines markets where public and private firms compete directly. Most theoretical work in this area focuses on mixed duopoly models where public firms maximize welfare while private firms maximize profits (Cremer et al., 1991; Matsumura, 1998; De Donder and Roemer, 2009; De Fraja and Valbonesi, 2009; Klumpp and Su, 2019). In healthcare specifically, studies have examined quality competition between public and private hospitals under price regulation (Herr, 2011; Sanjo, 2009), location choices in mixed hospital markets (Hehenkamp and Kaarbøe, 2020), and the welfare effects of market concentration when public and private providers coexist (Bisceglia et al., 2023). However, this literature has been largely theoretical, with limited empirical evidence on the actual competitive dynamics between public and private providers. My paper provides novel empirical evidence on mixed public-private competition by estimating the causal effects of public hospital entry on private hospital investment decisions. The findings demonstrate that competitive outcomes in mixed markets depend on the specific characteristics of public providers, particularly whether they generate complementarities that benefit private competitors or simply create substitution effects

My results also add to the broader literature on place-based policies (Glaeser and Gottlieb, 2008; Freedman, 2013; Busso et al., 2013; Kline and Moretti, 2014; v. Ehrlich and Overman, 2020; Juhász et al., 2024), which typically emphasize subsidies (Cingano et al., 2023), labor policy changes (Criscuolo et al., 2019) or historical infrastructure projects (Mitrunen, 2024; Garin and Rothbaum, 2024) as policies to stimulate regional economic development. In contrast, my findings highlight how public firms—in this case, public hospitals—can act as an alternative place-based investment that fosters private sector investments. Public hospitals effectively crowd in private hospitals by reducing hiring constraints through workforce training and offering complementary services that spur demand. This complementarity shows that place-making policies can extend beyond conventional infrastructure or tax subsidies to strategically place public facilities that strengthen local markets and generate spillover effects for private investment.

Finally, this paper adds to the hospital competition literature by examining a setting outside the United States. Most of the literature in the United States emphasizes insurance-driven negotiated prices (Kessler and McClellan, 2000; Ho, 2009; Gaynor et al., 2014; Ho and Lee, 2017, 2019). In many developing countries, patients often pay for hospital care out-of-pocket, and government-led initiatives can play a prominent role in shaping local market structures. Consequently, this fundamental difference leads to difficulties in extrapolating US-based studies to global health care markets. While prior research in India underscores the importance of understanding the role of informal providers, mixed payment mechanisms, and trust in healthcare markets (Das and Hammer, 2007; Das et al., 2008; Wagner et al., 2019; Banerjee et al., 2024; Jain, 2024) and studies in China highlight policies have encouraged public and private hospitals to compete for patients (Eggleston et al., 2008), few have modeled the demand and supply decisions of both public and private providers in a lower- or middle-income country context. This paper is the first to estimate both demand and entry in such a market and assess the trade-offs of multiple policies in a mixed healthcare market.

The paper proceeds as follows. Section 2 provides context and data on the Malaysian public and private hospital industry. Section 3 lays out important descriptive facts about the public-private hospital market. I then provide a conceptual framework based on the descriptive facts in Section 4, and then present the reduced form results in Section 5. Section 6 estimates the model to recover the entry costs, and Section 7 concludes.

2 Context and Data

2.1 History of the Public-Private Malaysian Health System

Following Malaysia's independence from the British Empire in 1957, the Ministry of Health established a network of public hospitals to ensure universal access to healthcare services. This public system operated as the dominant healthcare provider until the 1980s, when Malaysia adopted a series of broader economic liberalization policies extended to the healthcare sector.

The privatization wave of the early 1980s was a key policy shift in Malaysia's health system. The government actively encouraged private investment through tax breaks for medical devices and private health insurance (Barraclough, 2000). These nationwide policies allowed private investors to enter markets based on profit considerations rather than central planning directives.

However, by the mid-1990s, political resistance to healthcare privatization emerged as a constraint on further market oriented policies. The government's initial plans to corporatize public healthcare services faced significant opposition from the ruling coalition's constituents, who viewed potential reductions in subsidized public healthcare as a threat to equitable medical care.[5] This political backlash resulted in a policy reversal that reinforced the government's commitment to maintaining a robust public healthcare system alongside the growing private sector.

The 1995 general election became the pivotal moment that shaped Malaysia's public-private healthcare system. Rather than pursuing further privatization of public services, the government responded to electoral pressures by expanding public hospital capacity and reaffirming subsidized healthcare as a core public good. As a result, Malaysia developed hospital markets where private hospitals operate as an expensive alternative to a heavily subsidized public system, rather than as replacements for public provision.

Importantly for the event studies, the government's renewed commitment to public hospital expansion post-1995 provides an empirical opportunity to examine the effects of public hospitals on private investment. The construction of public hospitals following the electoral mandate creates variation in public hospital entry location and timing, which I use in the event study analyses to identify causal effects on private hospital entry.

[5] In 1985, Prime Minister Mahathir Mohamad announced a series of privatization and corporatization policies across multiple industries. This led to political concern from the main coalition's constituents, as the government contemplated reducing subsidized public healthcare services. In the 1995 Malaysia general elections, the government retracted all policies related to corporatizing public healthcare services and increased the number of public hospitals to show commitment to retaining a public-dominant health system Barraclough (1997, 2000).

2.2 Regulation, Physician Training, and Private Hospital Pricing

Public hospital allocation follows a multi-tiered process embedded within Malaysia's five-year development planning cycle. In the first stage, hospital funding is allocated to districts based on the Malaysia Plans, which are comprehensive national development blueprints that prioritize healthcare accessibility and population coverage. The Ministry of Health collaborates with State Economic Planning Units to identify districts requiring new healthcare infrastructure based on demographic projections, existing facility capacity, and accessibility gaps (see Figure A.8 for excerpts from official planning documents emphasizing health care accessibility). After districts receive funding allocations through this centralized planning process, the second stage involves selecting specific locations within the designated district. Local health authorities work with district officials to identify location sites that maximize population access while considering factors such as land availability, transportation networks, and proximity to existing health facilities.

In contrast, private hospital entry operates under a more lax regulatory framework established by the Private Healthcare Facilities and Services Act 1998. While the Ministry of Health retains approval authority for private hospital licenses, the regulatory standard primarily requires demonstration of sufficient local demand rather than adherence to national planning objectives. Private hospitals can choose any location within a district based on commercial considerations such as population density, income levels, and competitive positioning. In short, private entrants seek to make profits, while public hospitals are centrally allocated based on accessibility objectives.

Like many developing countries where the public sector dominates healthcare provision, Malaysia requires all physicians to complete a mandatory two-year housemanship program in public hospitals before practicing independently. This creates a direct pipeline from public hospital training programs to employment in both sectors. After completing housemanship, physicians choose between public sector employment (offering civil service job security and fixed salaries) and private practice opportunities with fee-for-service compensation.

Specialist training follows the same pattern. All physicians seeking specialization must complete residency programs in public hospitals, regardless of where these specialists plan to practice afterward. This institutional arrangement allows specialist public hospitals to serve dual purposes. Hospitals serve as both healthcare providers and essential training centers for the entire healthcare labor market, producing personnel who subsequently work across both public and private sectors.

The regulatory framework governing pricing differs between sectors. Public hospitals operate under a unified national pricing structure, with the government setting standardized fees for all services across the country but varying by room types. These prices are heavily subsidized. For example, any inpatient condition treated in a public hospital costs

Malaysian citizens MYR 100 (approximately USD 24) for a normal delivery in a third-class ward.

Private hospitals face a more complex regulatory environment. While the 1998 Act establishes fee schedules for physician consultations and medical procedures, it does not regulate hospital-specific charges such as room fees, meals, and ancillary services. This partial price regulation allows private hospitals significant flexibility to price their services based on local market conditions and competition. As a result, private hospitals charge significantly higher prices than public hospitals for similar services.

2.3 Data

I provide a brief overview of the data used in the event study analyses and structural model separately; further details can be found in Appendix A. A summary of the key variables is tabulated in Table A.1. The event study data comes from a combination of administrative data and surveys conducted by the Ministry of Health. The structural model combines aggregated electronic health records with hospital maternity package prices that I collected in 2022, and micro moments from a survey of families planning to have children.

Event Study Data. I estimate my events studies of new public hospital construction on private hospital entry using a district-level panel data spanning 132 districts over 1996-2013. The analysis focuses on 25 new public hospitals that began operations between 1996 and 2013, and their impact on the stock of private hospitals across districts. By 2013, there were 269 hospitals total in the sample: 135 public and 134 private. I construct this panel using data from the National Healthcare Establishment and Workforce Survey (NHEWS), which contains information about every hospital providing hospitalization services that was operational in 2013. Using each hospital's construction and opening dates, I backfill the count of public and private hospitals operating in each district for every year from 1996 to 2013.

The final dataset includes all general and specialized hospitals providing acute curative care from both public and private sectors. I exclude specialized institutions (prison, defense, and education ministry hospitals) and long-term care facilities (rehabilitative and palliative care hospitals, nursing homes, leprosy centers, and psychiatric institutions).

To understand the mechanisms driving private hospital entry patterns, I use two additional outcome data measured at the district level. Data on private physicians comes from the Population and Housing Census for 1970, 1980 and 1991. I use district-level counts of self-employed physicians as a proxy for private physicians, since all public physicians are civil servants receiving wages rather than operating independently.

Data on private hospital utilization comes from the National Health and Morbidity Survey conducted in 1996, 2006, and 2011. This nationally representative survey interviews approximately 59,000 respondents in 1996 and 2006, while 29,000 in 2011. The survey asks about healthcare utilization in the previous year, including private inpatient admissions. The survey weights allow for district-level estimation of private hospital utilization rates. I carry forward values to fill the missing years between survey rounds, yielding 396 district-year observations (132 districts $\times$ 3 years) for this analysis. These surveys are used by the Ministry of Health for planning purposes, providing confidence in their reliability and comparability across survey years.

Finally, I use 'Health Facts', an annual publicly available dataset containing hospital-level information on total beds from 2003-2013, to construct an alternative treatment of hospital upgrades. Health Facts covers the same hospitals as NHEWS, allowing me to identify existing hospitals that received significant capacity upgrades (defined as increases in bed count). I observe 49 such upgrades across different hospitals during this period. This alternative treatment tests whether the private hospital entry effects are specific to entirely new public hospital construction, or also occur when existing public hospitals expand their capacity.

Structural Model Data. I use four data sources for demand estimation and the dynamic entry model. My data covers 95 districts (out of 133 possible districts, see Figure C.4) after dropping areas with missing survey coverage or hospital price data.

I obtain hospital admissions data from the Ministry of Health's electronic health records systems. Public hospital admissions come from the *Sistem Maklumat Rekod Pesakit* (SMRP), while private hospital admissions come from the Private Hospital Discharge Database (PHDD). Both systems record patient demographics, diagnosis codes, admission and discharge dates, and treating hospital for all admissions in 2013. I use ICD-10 diagnosis codes to identify patients admitted for normal vaginal deliveries, which serves as the main dataset for demand estimation. The 2013 timing requires backprojecting demand patterns for the dynamic entry model.

Consumer preferences and demographic characteristics come from the National Health and Morbidity Survey (NHMS) 2015. The survey includes approximately 15,000 families with childbearing intentions across the 95 districts in my estimation sample. For respondents planning to have children, the survey elicits stated preferences about hospital choice for delivery, including quality perceptions (measured on Likert scales), waiting time concerns, and other choice factors. I geocode respondents' locations and match them to all available hospitals in their district, calculating straight-line distances to construct individual-to-hospital choice sets for the random coefficients logit demand estimation. These survey responses provide the micro moments for BLP estimation.

I conduct primary data collection in 2022 to compile hospital-specific prices for normal delivery packages. Private hospitals advertise flat-fee maternity packages through websites and social media, differentiated by room type and services. I collect the minimum advertised price for each private hospital through direct contact, website research, and social media monitoring. Private hospitals that did not respond (27 hospitals across 14 districts) are dropped from the demand estimation sample. Public hospitals charge a standardized subsidized rate of RM100 for normal delivery in third-class wards. I assume that relative price differences across hospitals remain stable when backprojected to 2013 for demand estimation. This assumption could be problematic if there were systematic changes in pricing strategies during 2013-2021. However, the continued growth of private hospitals from 134 to 202 by 2021 with minimal exits suggests an increasingly competitive and profitable market, meaning 2021 prices may underestimate historical price levels.

Land price data comes from the National Property Information Centre (NAPIC) for 2013, providing commercial land prices per square foot for each district. This data serves as a proxy for fixed sunk costs in the supply-side estimation.

3 Descriptive Facts

In this section, I lay out some key facts about the public-private hospital market in Malaysia.

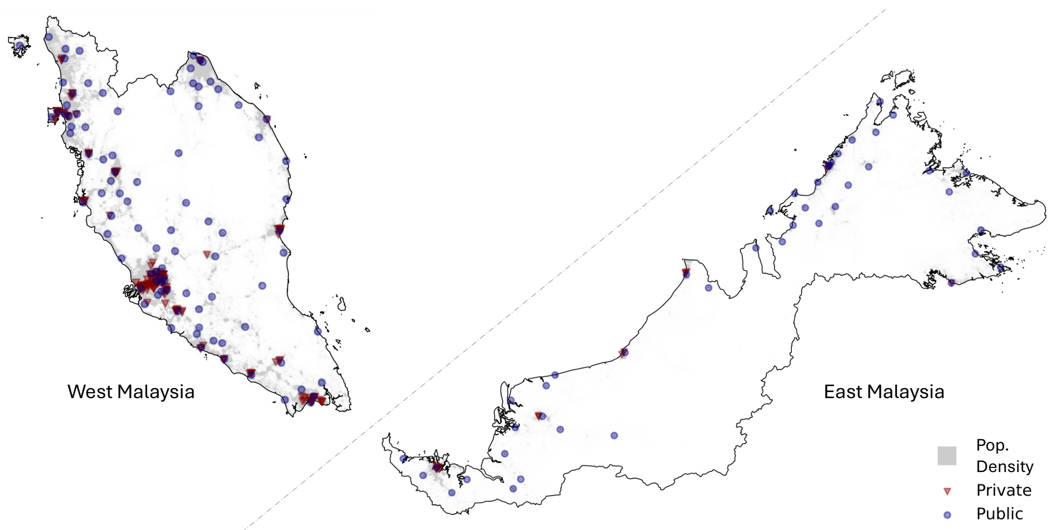
Private hospitals concentrate in urban areas while public hospitals distribute more evenly across the country. Figure 1 maps hospital locations in 2013 against population density, showing this clustering pattern. Figure A.3 shows how this geographic pattern has changed over time. Between 1982 and 2013, private hospitals expanded primarily in urban centers while public hospitals grew in rural areas.

Despite their urban concentration, private hospitals operate at a significantly smaller scale and capture limited market share. Private hospitals average only 94 beds compared to 509 beds for public specialist hospitals. For maternity services, private hospitals hold just 8 percent of district market share for vaginal deliveries, while public specialist and non-specialist hospitals capture 70-79 percent. This small market share occurs despite public specialist hospitals facing congestion. Public specialist hospitals exhibit 73.9 percent bed occupancy compared to 47.3 percent for public non-specialist hospitals and 53.9 percent for private hospitals. The congestion creates wait time dissatisfaction among public hospital patients (3.23 vs 3.82 satisfaction rating for private hospitals), yet survey respondents still rate public hospitals higher on overall quality (4.03 vs 3.83 for private hospitals).

The limited overlap between public and private hospitals partly reflects their focus in segmented price markets. Private maternity services cost 3,306 MYR compared to 100 MYR for subsidized public services—a 33-fold differential. This price gap corresponds to differences in the patient populations they serve. Private hospital users have higher monthly incomes (2.54 vs 1.52 thousand MYR), shorter travel distances to private facilities (15.31 vs 31.82 km), and higher private insurance rates (0.52 vs 0.16).

These differences extend to location decisions. Before estimating the causal effects of new public hospitals on private entry, I examine whether public hospital placement

Figure 1: Public and Private Hospitals Location in 2013

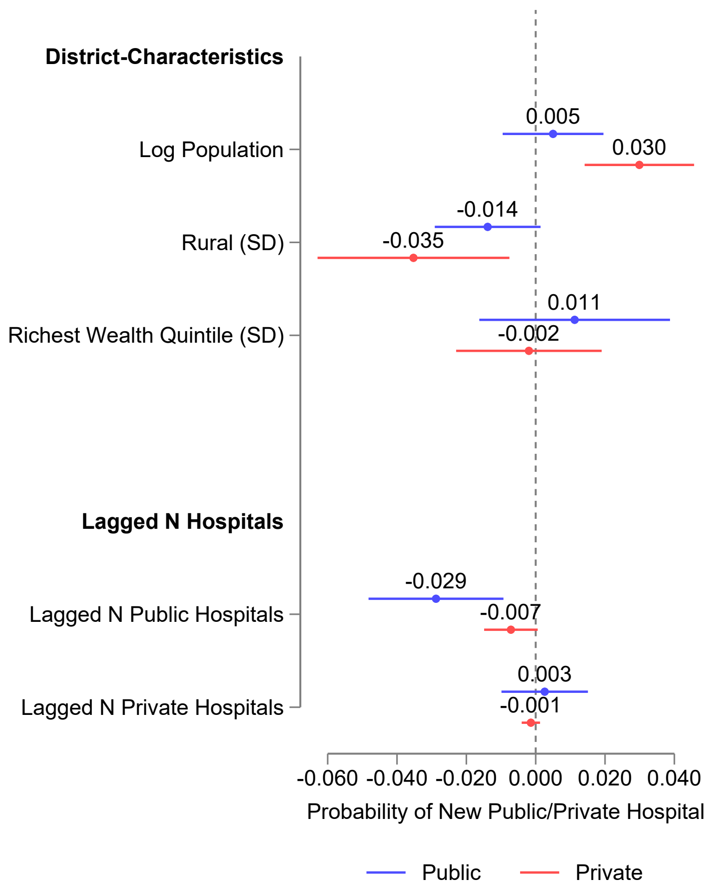


Note: Hospital location data are from the National Healthcare Establishment Workforce Survey (2013). Population density are 1km grids from the Center for Integrated Earth System Information (CIESIN).

correlates with factors that also drive private entry decisions. If public and private hospitals systematically locate in similar types of districts, this could confound my identification strategy. Figure 2 presents the average marginal effects of various district characteristics on the probability of public and private hospital entry from a logit model with year fixed effects. I omit district fixed effects to compare the characteristics of districts that received a new hospital to those that did not within the same year.

The results show distinct location patterns. Private hospitals systematically enter districts with higher population and lower proportion of rural residents. Public hospitals, conversely, are significantly less likely to enter districts that already have a public hospital, consistent with the Ministry of Health's stated objective of expanding access to underserved areas rather than duplicating existing public capacity. Notably, factors that strongly predict private entry such as population and rurality show weaker or statistically insignificant associations with public hospital allocations.

Figure 2: Descriptive Evidence on Public and Private Hospital Entry



Note: These are average marginal effects from logit regressions of public (or private) hospital entry on a set of district characteristics with year fixed effects. The data consists of public and private entry between 1996 and 2013. The mean probability for public entry is 0.012 while it is 0.031 for private hospitals. The full coefficient plot can be found in Figure A.5. The dependent variable is a binary variable for whether a district-year receives a new public (or private) hospital. These are selected statistically significant coefficients from the regression output. Standard errors are clustered at the district level.

4 Conceptual Framework

Given the descriptive facts from Section 3, I provide a framework to show how a new public hospital influences private hospital entry. The framework highlights the competition and complementarities between the public and private sector. I provide a sketch of the model here while the full estimation and simulation details are presented in Section 6.

4.1 Market Setup

Consider a geographically localized healthcare market initially serviced by one public hospital. The public hospital operates with two distinct types of capacity investments: bed capacity K_g^B for patient care and training capacity K_g^T for physician education programs. Public hospitals serve a dual function of providing healthcare services to patients while simultaneously training new physicians through mandatory residency and specialty programs. Increasing bed capacity K_g^B would decrease demand for private entrants, while increasing K_g^T would thicken the labor pool of physicians.

4.2 Private Hospital Costs and Entry Decisions

A set of potential private hospital entrants $h \in \mathcal{H}$ considers market entry based upon heterogeneous fixed entry costs F_h, independently drawn from a known cumulative distribution $G(F)$. Private hospitals face two types of fixed costs. First, F_s is the sunk cost of obtaining land and constructing a new hospital building. Second, $F_o(L^t)$ is the fixed operational cost that depends on the number of physicians within a market. Increasing the physician labor pool reduces these fixed costs as hiring physicians becomes easier: $F_o'(L^t) < 0$. The fixed operational cost represents the minimum number of physicians the hospital must hire to provide healthcare services. The profit function for private hospital h is:

$$\Pi_h = D_h \cdot (p_h^* - c_h) - F_s - F_o(L^t) \tag{1}$$

where D_h represents demand for private hospital services, p_h^* is the profit-maximizing price, and c_h represents variable costs. Private hospitals enter when expected profits exceed their total fixed costs, giving the entry condition:

$$F_s + F_o(L^t) \leq \pi_h^*(K_g^B, K_g^T) \tag{2}$$

where $\pi_h^*(K_g^B, K_g^T) = \max_{p_h} \pi_h$ represents maximum achievable private profits as a function of local physician supply L^t. Given the distribution of entry costs $G(F)$, the equilibrium number of private entrants is: $N = G(\pi_h^*(K_g^B, K_g^T))$

4.3 Crowd-In versus Crowd-Out Mechanisms

The relationship between public hospital capacity and private entry operates through two primary channels that work in opposite directions. Public hospitals consists of two distinct types of capacity: bed capacity K_g^B that determines how many patients can be treated, and physician training capacity K_g^T that determines how many doctors can be trained simultaneously. Bed capacity directly affects the demand available to private hospitals through competition: $\frac{\partial D_h}{\partial K_g^B} < 0$. Training capacity affects the local physician labor supply that private hospitals need to hire from: $\frac{\partial L^t}{\partial K_g^T} > 0$ and $\frac{\partial F_o}{\partial L^t} < 0$.

Labor Market Crowd-In Effect. Public hospitals increase the local supply of trained physicians L^t through their mandatory training programs. When public hospital training capacity K_g^T expands, it increases physician supply, which reduces private hospitals' fixed operational costs $F_o(L^t)$, making entry more profitable:

$$\frac{\partial N}{\partial K_g^T} = \underbrace{\frac{\partial N}{\partial F_o}}_{(-)} \cdot \underbrace{\frac{\partial F_o}{\partial L^t}}_{(-)} \cdot \underbrace{\frac{\partial L^t}{\partial K_g^T}}_{(+)} > 0 \quad \text{(Labor Market Crowd-In)} \tag{3}$$

Competition Crowd-Out Effect. When public hospital bed capacity K_g^B expands, it takes away demand from the private sector by providing more accessible public care, reducing private hospital profitability:

$$\frac{\partial N}{\partial K_g^B} = \underbrace{\frac{\partial N}{\partial D_h}}_{(+)} \cdot \underbrace{\frac{\partial D_h}{\partial K_g^B}}_{(-)} < 0 \quad \text{(Competition Crowd-Out)} \tag{4}$$

When new public hospitals are constructed, both bed capacity and training capacity typically increase simultaneously. The overall effect on private entry is:

$$\frac{\partial N}{\partial(\text{New Public Hospital})} = \underbrace{\frac{\partial N}{\partial K_g^B} \cdot \Delta K_g^B}_{\text{Competition Effect}} + \underbrace{\frac{\partial N}{\partial K_g^T} \cdot \Delta K_g^T}_{\text{Labor Market Effect}} \tag{5}$$

where ΔK_g^B and ΔK_g^T represent the increases in bed and training capacity from new hospital construction. Crowd-in effects dominate when:

$$\underbrace{\frac{\partial N}{\partial K_g^T} \cdot \Delta K_g^T}_{\text{Labor complementarities}} > \underbrace{\left| \frac{\partial N}{\partial K_g^B} \cdot \Delta K_g^B \right|}_{\text{Competition effects}}$$

This occurs when physician complementarities from thickened labor markets are large relative to bed capacity expansion. Crowd-out effects dominate when bed capacity expansion significantly reduces private demand and physician complementarities are weak.

The framework generates several testable predictions. First, new public hospitals should have heterogeneous effects on private hospital entry depending on the relative strength of physician training versus service capacity expansion. Second, crowd-in effects should be stronger for new hospitals that significantly expand local physician training. Third, crowd-out effects should be stronger when new public hospitals significantly expand service capacity in previously underserved areas with substantial unmet demand.

5 Reduced Form Evidence

5.1 Impact of New Public Hospitals on Private Entrants

Identifying the impact of new public hospitals on private entrants requires addressing the endogenous timing and location of public hospital placement. The Ministry of Health strategically allocates public hospitals by selecting districts based on their accessibility to existing health facilities, population size, and congestion levels at existing public facilities. Since these same factors may influence private hospital entry decisions, they potentially confound the effects of public hospital construction on private entry.

Figure 2 provides some reassurance that public and private hospitals respond to distinct location incentives. Public hospitals are allocated to districts lacking existing public facilities and urban areas, while private hospitals locate in districts with high population growth, urban settings, educated populations, and established private specialist networks. Although some overlap exists in preferences for urban locations, this evidence reveals that public and private hospitals respond to fundamentally different market signals.

These distinct entry patterns form the foundation of my identification strategy. I exploit the Ministry's systematic allocation process by using never-treated districts as controls, as these districts will likely receive public hospitals eventually, but remain untreated within my observation window from 1996 to 2013. As a robustness check below, I also use the last-treated cohort as an alternative control group, which compares early-treated districts to those treated at the end of the sample period.

Specifically, my main empirical design uses a staggered event study that exploits variation in the timing of public hospital construction across districts. I define treatment units as the 25 districts receiving new public hospitals between 1996 and 2013, while I use 22 districts receiving no public hospitals by 2013 as control units (Figure B.1 maps these districts).

The validity of this empirical strategy depends on the balance between treatment and control groups. Table 1 shows strong pre-treatment balance across most dimensions when comparing 1991 characteristics. The groups exhibit balance on key covariates including wealth distribution, education levels, ethnicity shares, labor force participation, and existing health infrastructure. Chinese ethnicity, which is particularly important given its association with higher private healthcare utilization, appears well-balanced between groups (Ministry of Health Malaysia, 2016). However, treated districts show modest imbalances on three characteristics: they have significantly larger populations, lower rurality, and are slightly younger on average.

While I observe modest and only marginally significant imbalances, they could bias my estimates upward since population and urbanization and a younger population could predict higher private hospital entry. I begin with a standard event study specification

Table 1: Pre-Treatment Summary Statistics by Treatment Status in 1996

Variable	Treated	Never Treated	Difference	P-value
Panel A. Demographics				
Log Population	11.754 (1.115)	11.057 (1.106)	0.697	0.037
Rural Population Share	0.602 (0.310)	0.782 (0.312)	-0.180	0.063
Average Age	23.717 (2.043)	25.258 (2.536)	-1.541	0.031
Female Share	0.482 (0.024)	0.497 (0.039)	-0.015	0.123
Chinese Share	0.215 (0.151)	0.200 (0.194)	0.015	0.773
Malay Share	0.416 (0.306)	0.447 (0.354)	-0.031	0.752
Indian Share	0.071 (0.080)	0.047 (0.063)	0.024	0.281
Labor Force Participation	0.632 (0.058)	0.642 (0.104)	-0.010	0.669
Panel B. Socioeconomic Status				
Poorest	0.434 (0.260)	0.494 (0.286)	-0.060	0.476
Middle	0.307 (0.129)	0.293 (0.153)	0.014	0.733
Richest	0.258 (0.181)	0.213 (0.205)	0.045	0.446
Panel C. Education				
College/University	0.021 (0.020)	0.021 (0.033)	0.000	0.968
Secondary Completed	0.226 (0.080)	0.222 (0.079)	0.004	0.867
Primary Completed	0.201 (0.041)	0.194 (0.041)	0.007	0.617
Some Primary Education	0.201 (0.030)	0.204 (0.034)	-0.003	0.766
Panel D. Health Facilities				
Dist. to Pub Hosp (km)	36.522 (28.627)	41.423 (40.336)	-4.901	0.630
Dist. to Pri Hosp (km)	102.979 (105.322)	106.691 (112.125)	-3.712	0.907
N Public Hospitals	0.320 (0.557)	0.182 (0.395)	0.138	0.338
N Private Hospitals	0.680 (1.725)	0.273 (0.935)	0.407	0.329
N Specialist Physicians	0.050 (0.111)	0.018 (0.058)	0.032	0.266

Notes: This table compares the 25 treatment districts with the 22 never treated districts based on pre-treatment characteristics in 1991. Standard deviations in parentheses. Unit of observation is districts. All data from the 1991 Malaysian Census and hospital panel data. Distances are straight-line kilometers to facilities calculated using 1km population grids and collapsing at the district level. Wealth quintiles are constructed from household assets (electricity, water supply, telephone, automobiles, air conditioning, washing machine, refrigerator, television, VCR, radio, toilet, wall material).

to transparently assess the magnitude and significance of treatment effects, then verify robustness through balancing regressions, synthetic difference-in-differences (Arkhangelsky et al., 2021) and matching approaches that control for observed differences.

I measure my primary outcome as the cumulative count of private hospitals operating in each district-year. My estimation strategy uses the interaction-weighted estimator from Sun and Abraham (2021a) to address treatment effect heterogeneity in this staggered adoption setting. Traditional two-way fixed effects estimators are contaminated when treatment effects vary across cohorts and time periods. To address these concerns and ensure my estimates represent interpretable weighted averages of cohort-specific treatment effects, I estimate the following event study specification:

$$Y_{dt} = \delta_d + \lambda_t + \sum_{e<\infty} \sum_{\ell \neq -1} \delta_{e,\ell} \, \mathbf{1}\{E_d = e\} \, D_{dt}^{\ell} + \varepsilon_{dt} \tag{6}$$

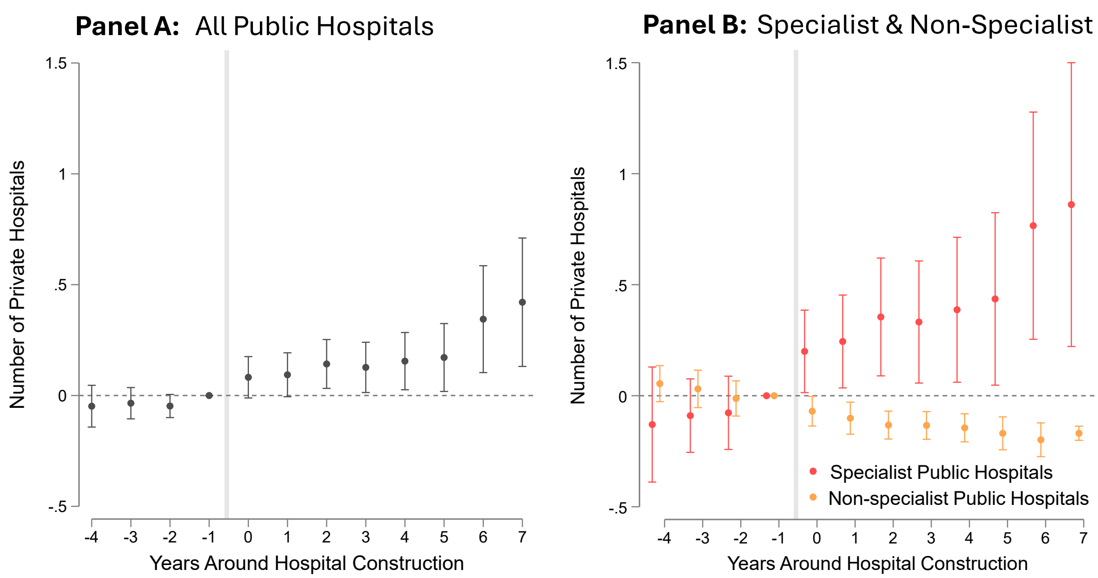
where Y_{dt} is the number of private hospitals in district d in year t, δ_d and λ_t are district and year fixed effects, E_d is the year district d receives its first public hospital during the sample period 1996-2003 (with $E_d = 0$ for never-treated districts that receive no public hospital by 2013), and $D_{dt}^{\ell} = \mathbf{1}\{t - E_d = \ell\}$ is an indicator for being ℓ years relative to public hospital opening. The cohorts $e \in \{1997, 1998, ..., 2003\}$ represent districts grouped by the year they first received a public hospital. I include relative time indicators for $\ell \in \{-10, ..., -2, 0, ..., 16\}$, excluding $\ell = -1$ as the reference period. Each coefficient $\hat{\delta}_{e,\ell}$ estimates the cohort-specific average treatment effect on the treated ($CATT_{e,\ell}$) using the never-treated districts as the comparison group. Following Sun and Abraham (2021b), I then construct interaction-weighted estimates $\hat{\nu}_\ell$ by taking weighted averages of the $\hat{\delta}_{e,\ell}$ coefficients across cohorts, with weights equal to each cohort's share among districts that experience at least ℓ years of exposure to public hospital presence.

The district fixed effects δ_d absorb all time-invariant differences across districts, such as baseline differences in income levels, population size, or pre-existing healthcare infrastructure that might affect private hospital entry. The year fixed effects λ_t capture shocks that are common to all districts in a given year. Remaining variation comes from comparing how the trajectory of private hospital entry in treated districts evolves around the year of public hospital construction, relative to the contemporaneous trends in never-treated districts.

The conceptual framework suggests that the effects of public hospitals on private entry may vary by hospital type. Specialist public hospitals, which provide specialist physician training programs, may generate positive spillovers that encourage private hospital entry. In contrast, non-specialist public hospitals, which primarily offer general inpatient and emergency services, may compete directly with private hospitals and deter entry without offering much complementarities in local labor markets. Thus, I estimate three separate event studies: one pooling all public hospitals, one using only specialist public hospitals as treatment, and one using only non-specialist public hospitals as treatment. For districts receiving multiple public hospitals during the sample period[6], I use the first treatment for the main analysis and explore robustness below.

In Figure 3, I present the event study estimates of the impact of new public hospitals on the number of private hospitals in the same district. Panel A uses all public hospitals as the treatment, while Panel B segregates the treatment to specialist and non-specialist hospitals. I truncate the figure to show four pre-period lags and seven post-period event study estimates, with the reference period at $\ell = -1$. I also provide a table of the average of the full set of post-treatment coefficients in Table 2.

Figure 3: Effects of New Public Hospitals on Number of Private Hospitals



Note: This figure presents four period lags and seven post-period event study estimates from Equation 6. The estimates come from the impact of 25 new public hospitals on the number of private hospitals within the same district. Each dot represents a point estimate with the corresponding 95% confidence interval shown as vertical lines. Standard errors are clustered at the district level.

Panel A of Figure 3 shows parallel pre-trends across all hospital types, with coefficients close to zero and statistically insignificant in the four years before public hospital construction. Post-construction, the average effect is positive and immediate, with public hospitals increasing private hospital counts by 47 percent over the post-treatment period (0.465 relative to a pre-treatment mean of 0.979). These estimates conflate substantial heterogeneity by hospital type as shown in Panel B. Specialist public hospitals generate immediate and sustained crowd-in effects on private hospital entry, with the effect growing from approximately 0.5 additional private hospitals in the first year to over 1 private hospital by

[6]Three districts had more than one public hospitals built between 1996 and 2013.

Table 2: Average Post-Treatment Effects on Private Hospitals

	Number of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	0.465		
	(0.094)		
E2: Specialist public hospitals		0.785	
		(0.108)	
E3: Non-specialist public hospitals			-0.171
			(0.009)
Mean Dep. Var.	1.302	1.701	0.631
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N Districts $\times$ Year	846	648	594
R^2	0.951	0.954	0.930
Unique Events	25	14	11
Estimator	SA	SA	SA

Notes: Each column presents results from separate regressions using the Sun and Abraham (2021) estimator. Coefficients represent the average post-period treatment effects from the interaction-weighted estimator. Standard errors in parentheses are clustered at the district level. The dependent variable is the number of private hospitals in a district. Column (1) includes all public hospitals; columns (2) and (3) separate by public hospital type.

year six. The table estimates (Column 2) show that specialist hospitals increase the number of private hospitals by 61.5 percent on average over the post-treatment period.

In contrast, non-specialist public hospitals produce immediate crowd-out effects that persist throughout the post-treatment period. These hospitals reduce private hospital entry by approximately 0.3-0.5 hospitals across all post-treatment years, with the table showing an average reduction of private hospitals by 56 percent. The opposing signs and statistical significance of these effects provide suggestive empirical evidence of specialist hospitals creating specialist physician training complementarities that benefit private practice, while non-specialist hospitals primarily expand basic service capacity that competes directly with private providers. Below, I provide a direct test of this mechanism by examining the effects on private healthcare utilization and private physician supply.

5.2 Robustness Checks

To ensure the robustness of the main findings, I conduct several robustness checks that address potential concerns about the empirical design and estimation approach.

Balancing Regressions. I first provide a two-step balancing regression that shows how the event study design addresses endogeneity concerns from the relationship between district demographics, public health construction and private hospital entry. To do this, I first predict the number of private hospital within a district using the same demographic variables in Table 1. Next, I examine how public hospital construction at the district-year level correlates with this predicted measure. The key idea is, if public hospital construction is correlated with unobserved determinants of private hospital entry, then we should see a significant correlation between public hospital construction and the predicted private hospital count. However, if the event study design adequately controls for these confounders, then this correlation should be small and statistically insignificant.

Figure B.3 plots the results. Each set of coefficients represent separate treatment types: all types of public hospitals, specialist public hospitals and non-specialist public hospitals separately. Each dot represents a point estimate from Equation 6, where 'Cross-Section' represents the correlation between public hospital construction and the predicted private hospital count without any fixed effects. The remaining estimates add district fixed effects, year fixed effects, and both district and year fixed effects sequentially.

The results show that without any fixed effects, public hospital construction is positively correlated with predicted private hospital counts, suggesting that public hospitals are more likely to be built in districts with higher underlying demand for private hospitals. However, once I include district fixed effects, this correlation becomes small and statistically insignificant across all treatment types. Adding year fixed effects does not change this result. This evidence suggests that the event study design effectively controls for confounding factors that might bias the estimates.

Synthetic Difference-in-Differences. The balance table shows some differences in pre-treatment characteristics between treatment and control districts, particularly in population size and rurality. Given this, I test the robustness of my main results using a staggered synthetic difference-in-differences approach (Arkhangelsky et al., 2021). The synthetic DiD estimator addresses key limitations of the standard event study approach by automatically reweighting control districts and time periods based on their predictive power for the outcome. This dual weighting mechanism provides a more credible counterfactual when treatment and control groups exhibit baseline differences, as in my setting. The details on the table and results are in Section B.3.

Table B.2 and Figure B.4 present the results using this method. The findings are consistent with the main specification. Specialist public hospitals significantly increase private hospital entry by 0.692 hospitals on average (compared to 0.785 in the main specification), while non-specialist public hospitals show negligible effects (-0.016 compared to -0.171 in the main specification). The dynamic effects displayed in Figure B.4 closely track the patterns from the main event study, with specialist hospitals driving gradual but persistent increases in private entry over time.

Matching. I also test the robustness of my main results using coarsened exact matching (CEM) to balance treatment and control districts on the two variables showing the largest pre-treatment imbalances: rurality and the number of existing public hospitals. See Section B.4 for details on the balancing, and results.

The matching procedure reduces the sample to 28 districts (12 treated, 16 control), but removes the statistically significant pre-treatment differences (Table B.3). Figure B.5 shows that the effect remains positive and significant at 0.108 additional private hospitals, representing a 31.4 percent increase relative to the matched sample's pre-treatment mean. This percentage effect closely mirrors the main specification (47.5 percent increase), providing additional confidence that pre-treatment imbalances do not drive the results. I focus on all public hospitals for this robustness check rather than disaggregating by type due to the substantial sample reduction that would compromise statistical power for subgroup analysis.

Multiple Treatment Districts. The main analysis uses the first treatment for districts that received multiple public hospitals during the sample period. To test whether this affects my main results, I exclude the three districts that received multiple treatments and re-estimate the main specification. I tabulate the post-treatment event study effects in Table B.4. The results show very similar coefficients to the main effects in Table 2.

Alternative Control Group. The main analysis uses never-treated districts as the control group. As noted above, I re-estimate the main event study results using the last-treated cohort as the control group, which provides a different identifying assumption that compares early-treated districts to those treated at the end of the sample period. I tabulate the post-treatment effects in Table B.5. The results are similar to the main findings, with public hospital entry leading to a significant increase in private hospital entry. Specifically, the introduction of all public hospitals increases private hospital count by 0.760 hospitals on average, representing a 77.6 percent increase relative to the pre-treatment mean of 0.979 hospitals. Specialist public hospitals alone generate an increase of 0.665 private hospitals, a 52.0 percent increase relative to the pre-treatment mean of 1.278 hospitals. However, the analysis for non-specialist public hospitals cannot be estimated due to insufficient variation in the last-treated group, as both control and treatment districts had zero private hospital entrants in this category.

Alternative Estimators. Table B.6 presents results using five different estimators designed for staggered difference-in-differences settings with heterogeneous treatment effects. I compare my main event studies results with the Borusyak et al. (2024) imputation estimator, Callaway and Sant'Anna (2021) group-time aggregation, de Chaisemartin and D'Haultfœuille (2024) estimator, and synthetic difference-in-differences (Arkhangelsky et al., 2021). Across all estimators, specialist public hospitals consistently show positive and generally significant effects on private hospital entry, while non-specialist hospitals show negative effects. The specialist hospital effects range from 0.558 to 1.424, with most estimates statistically significant. Non-specialist hospital effects range from -0.016 to -0.281, all negative but with varying precision.

5.2.1 Mechanism: Effects on Private Health Care Utilization and Private Physicians

To directly observe the channels through which public hospitals affect private hospital entry, I examine the effects on private healthcare utilization and private physician supply. Unlike the hospital count outcome which uses panel data over the full 1996-2013 period, the mechanism analysis is constrained by data availability. Private hospital admissions data are available for 1996, 2006, and 2011, while private physician data are available for 1970, 1980 and 1991[7]. Given these limited time points, I use a stacked 2x2 difference-in-differences specification rather than the full event study design. Control units are the same never-treated units as the main event study design, which are districts that are not treated by 2013. Treated units are stacked alongside control units, resulting in two stacks. For admissions, the first stack consists of treated units between 1996 and 2006, and the second consists of treated units between 2006 and 2011. For physicians, the first stack consists of treated units between 1970 and 1980, and the second consists of treated units between 1980 and 1991 (Cengiz et al., 2019; Deshpande and Li, 2019). In particular, for each district d, year t and stack s I estimate:

$$Y_{sdt} = \beta \cdot \text{Post}_t \times \text{Treated}_d + \alpha_{ds} + \lambda_{ts} + \varepsilon_{dt} \tag{7}$$

where Post_t indicates the period after public hospital construction and Treated_d indicates districts that received public hospitals during the sample period. Control units are the same as the event studies' never-treated units. The coefficient β captures the average treatment effect over the post-treatment period. Table 3 presents results for private hospital admissions per 10,000 admissions and on self-employed physicians, which I use to proxy for private specialist physician.

The stacked specification introduces district-by-stack fixed effects α_{ds}, which absorb all time-invariant differences across districts within each stack. This ensures that comparisons are made only within the same stack, controlling for persistent differences across districts that might otherwise bias estimates. The year-by-stack fixed effects λ_{ts} capture period-specific shocks common to all districts in the same stack. Remaining variation comes from comparing the change in outcomes between the pre- and post-construction periods in treated districts to the analogous change in never-treated districts within the same stack. In other words, the coefficient β is estimated from the difference-in-differences comparison of treated versus untreated districts before and after hospital construction, separately within each stack, and then combined across stacks. The results reveal distinct patterns by hospital type. Specialist public hospitals reduce private hospital admissions by 70 percent (0.299 per 10,000 hospital admissions), while non-specialist hospitals show a smaller, statistically

[7] While I do have access to census data from 2000, the lowest level of granularity for physician data would combine both physicians, veterinarians, dentists and other medical professionals

Table 3: Effects on Private Hospital Admissions and Specialists

	Private Hospital Admissions (10,000s)		Private Specialist Physicians (100s)	
	(1)	(2)	(3)	(4)
E2: Specialist public hospitals	-0.299		0.547*	
	(0.140)		(0.302)	
E3: Non-specialist public hospitals		-0.111		0.063
		(0.099)		(0.158)
Mean Dep. Var.	0.428	0.293	0.309	0.159
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	120	114	58	68
R^2	0.815	0.804	0.872	0.820
Unique Events	14	11	7	10
Estimator	TWFE	TWFE	TWFE	TWFE

Notes: Each column reports results from stacked difference-in-differences regressions. Columns 1-2 use private hospital admissions (in units of 10,000s) as the dependent variable, combining 1996-2006 and 2006-2011 periods. Columns 3-4 use self-employed physicians (in units of 100s) as the dependent variable using 1970, 1980, and 1991 census data. The stacked approach combines districts treated in the first period vs. never-treated (Stack 1) and districts treated in the second period vs. never-treated (Stack 2). Mean dependent variable represents the mean across all observations. Standard errors clustered by district are in parentheses. Rows correspond to specialist public hospitals (E2) and non-specialist public hospitals (E3). Hospital admissions data come from the National Health and Morbidity Survey. Physician data come from census records.

insignificant reduction of 38 percent (0.111 per 10,000). These different effects suggest specialist hospitals more directly substitute for private healthcare services.

Despite reducing demand for private hospital services, public hospitals increase the supply of private physicians through training complementarities. Each specialist public hospital increases private specialist physicians by 54.7 relative to the mean of 30.9. The mean dependent variable is smaller than the actual effect size, as there are many districts with no private specialist physicians. Non-specialist hospitals show essentially no effect on specialist physician supply. These estimates use a stacked design with three time periods (1970, 1980, 1991) and assume immediate effects of new public hospitals, though results are robust to alternative lagged effects (see Table B.1). The large magnitude of the specialist hospital effect, despite limited statistical precision due to small sample size, provides evidence that specialist hospitals create training opportunities that expand the pool of specialist physicians who subsequently establish independent practices.

These mechanism results help to explain the main findings. Although specialist hospitals reduce private hospital utilization through direct substitution, these hospitals generate positive labor spillovers that offset these negative demand effects, leading to net crowd-in of private hospital entry. The particularly strong effect of specialist hospitals on physician supply demonstrates how these facilities create valuable training opportunities that expand the overall healthcare market despite initially reducing private hospital demand.

5.3 Heterogeneous Effects by Hospital Size

The crowd-in effects of specialist public hospitals may vary across private hospital sizes if there are economies of scale in leveraging specialist physician supply. To examine this, I estimate Equation 6 separately for three hospital size categories based on bed capacity: small hospitals (fewer than 50 beds), medium hospitals (50-100 beds), and large hospitals (over 100 beds).

Figure 4 presents the event study estimates. Panel A shows the effects of specialist public hospitals, while Panel B shows non-specialist effects. The results reveal substantial heterogeneity by hospital size for specialist hospitals, but relatively uniform effects for non-specialist hospitals. Table 4 summarizes the average post-treatment effects.

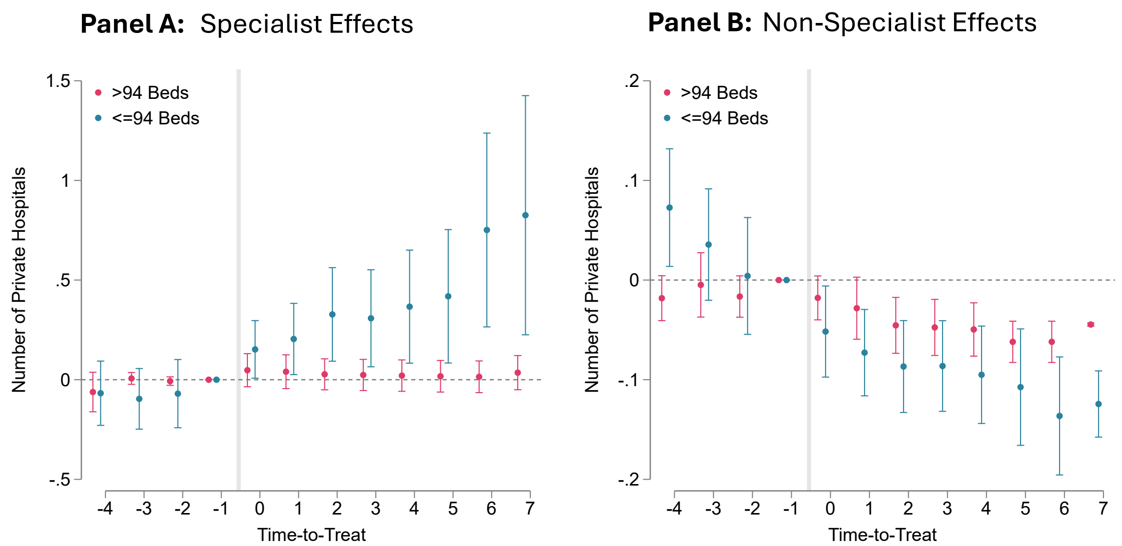
Specialist public hospitals generate the strongest crowd-in effects on small private hospitals, increasing their count by 0.532 hospitals on average (104 percent relative to the pre-treatment mean of 0.509). The effect attenuates sharply with hospital size: medium hospitals increase by 0.195 (49 percent), while large hospitals show a modest increase of 0.057 (7 percent). These declining effects suggest that the benefits from expanded specialist physician supply exhibit diminishing returns to scale.

Several factors explain why small hospitals respond most strongly to specialist public hospitals. First, small hospitals face lower entry barriers. These hospitals require fewer specialists to begin operations. Second, large private hospitals concentrate in urban areas where specialist supply is already relatively sufficient, reducing the marginal impact of additional public training. Third, small specialist hospitals tend to focus on less surgery-intensive services (Figure B.2).

In contrast, non-specialist public hospitals show relatively uniform crowding out across hospital sizes, with reductions ranging from -0.057 for small hospitals (44 percent) to -0.116 for medium hospitals (85 percent) to -0.059 for large hospitals (16 percent). The relatively consistent negative effects across sizes indicate that the competitive pressure from non-specialist public hospitals—which expand general inpatient and emergency services without specialist training programs—operates similarly across the private hospital size distribution. Unlike specialist hospitals, non-specialist facilities generate no offsetting labor supply benefits that might vary by scale, resulting in net crowding out regardless of hospital size.

These heterogeneous effects provide additional evidence for the specialist training mechanism underlying the main crowd-in results. The specialist physician supply shock generated by public hospitals disproportionately facilitates entry by small private hospitals, which face lower barriers to reaching operational scale. In contrast, the uniform crowding

Figure 4: Effects of Specialist and Non-Specialist Public Hospitals on Small and Large Private Hospitals



Note: This figure presents four pre-period and seven post-period event study estimates from Equation 6. Panel A shows the effects of 14 new specialist public hospitals on the number of small (fewer than 95 beds), and large (over 95 beds) private hospitals within the same district. Panel B shows the effects of 11 non-specialist public hospitals. Each dot represents a point estimate with the corresponding 95% confidence interval shown as vertical lines. The reference period is $\ell = -1$. Standard errors are clustered at the district level.

out from non-specialist hospitals confirms that competitive effects do not vary meaningfully by hospital size in the absence of training complementarities.

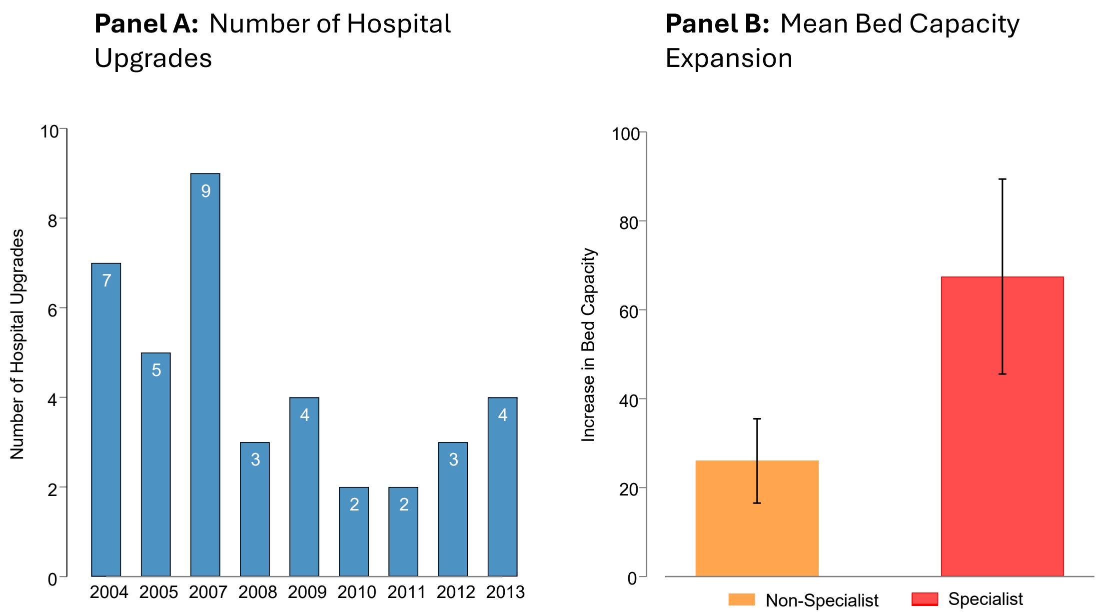
Table 4: Effects on Private Hospitals by Size

	Private Hospital Sizes					
	Small (1)	**Medium** (2)	**Large** (3)	**Small** (4)	**Medium** (5)	**Large** (6)
E2: Specialist public hospitals	0.532	0.195	0.057			
	(0.064)	(0.036)	(0.029)			
E3: Non-specialist public hospitals				-0.057	-0.116	-0.059
				(0.002)	(0.003)	(0.002)
Mean Dep. Var.	0.509	0.401	0.790	0.131	0.136	0.364
Observations	648	648	648	594	594	594
R^2	0.937	0.844	0.982	0.897	0.792	0.980
Unique Events	14	14	14	11	11	11
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	SA	SA	SA	SA	SA	SA

Notes: Each column presents results from separate regressions using the Sun and Abraham (2021) estimator. Coefficients represent the average post-period treatment effects from the interaction-weighted estimator. The dependent variable is the number of private hospitals in each size category within a district. Small hospitals have fewer than 50 beds, medium hospitals have 50-100 beds, and large hospitals have over 100 beds. Columns 1-3 show the effects of 14 specialist public hospitals; columns 4-6 show the effects of 11 non-specialist public hospitals. Standard errors in parentheses are clustered at the district level.

5.4 Impact of Public Hospital Upgrades on Private Entrants

Figure 5: Number of Public Hospital Upgrades by Year



Note: Data on hospital upgrades are from Health Facts published by the Ministry of Health, covering 2003-2013. Hospital upgrades are defined as expansions in bed capacity at existing public hospitals. Panel A shows the number of hospital upgrades by year. Panel B shows the average bed capacity expansion per upgrade.

To further isolate the mechanisms behind the main findings, I examine an alternative treatment that affects substitution without creating substantial new training opportunities. Public hospital upgrades, defined as expansions of existing facilities through additional beds, provide a test of whether the crowd-in effects of specialist hospitals operate through physician training complementarities or simply through expanded healthcare capacity.

Unlike new hospital construction, these upgrades expand the service capacity of existing facilities while generating limited additional training infrastructure, since teaching programs and physician training capacity are already established within these hospitals. If the crowd-in effects identified in the main analysis operate primarily through expanded training opportunities rather than general capacity expansion, one should expect hospital upgrades to generate smaller effects than new construction.

In Figure 5, I plot the number of hospital upgrades by year in Panel A, and the mean bed capacity expansion in Panel B. Between 2003 and 2013, 35 public hospitals underwent significant expansions, including 25 specialist hospitals and 11 non-specialist hospitals. I use districts that never received upgrades during the study period as control units. From Panel B, the mean bed capacity expansion differs across hospital types.

Table 5 presents the results. All hospital upgrades, specialist upgrades, and non-specialist upgrades show imprecisely estimated effects on private entry, making it difficult to draw strong conclusions about the mechanisms from the upgrade analysis.

However, the general pattern that upgrade effects appear smaller and less precise than the corresponding new construction effects provides some support for the training complementarity hypothesis. This difference suggests that creating entirely new training infrastructure has much larger spillover effects than marginally expanding existing training capacity. The modest positive effect of specialist upgrades indicates that some additional training opportunities may be created through capacity expansion, but these are insufficient to generate the strong crowd-in effects observed with new construction.

Non-specialist upgrades continue to crowd out private entry, consistent with the pattern observed for new non-specialist hospitals. This reinforces that non-specialist facilities generate competitive effects without meaningful training spillovers, regardless of whether they represent new construction or capacity expansion.

These results provide evidence for the training complementarity mechanism. While capacity expansion through upgrades can generate modest training benefits for specialist facilities, the creation of entirely new training infrastructure through hospital construction produces much larger spillover effects that dominate competitive pressures and drive private hospital entry.

Table 5: Effects of Public Hospital Upgrades on Private Hospital Entry

	Number of Private Hospitals		
	(1)	(2)	(3)
E1: All upgrades	0.138		
	(0.173)		
E2: Specialist upgrades		0.238	
		(0.215)	
E3: Non-specialist upgrades			-0.170
			(0.169)
Mean Dep. Var.	0.934	1.132	0.631
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1026	846	594
R^2	0.947	0.946	0.928
Unique Events	35	25	11
Estimator	SA	SA	SA

Notes: Each column presents results from separate regressions examining the impact of public hospital upgrades (2003-2013) using the Sun and Abraham (2021) estimator. Hospital upgrades are defined as expansions of existing bed capacities. The dependent variable is the number of private hospitals in a district. Control units are districts that never received upgrades during the study period. Standard errors in parentheses are clustered at the district level.

5.5 Impact of Specialist Public Hospitals on Private Entry Location

Thus far, the analysis has focused on district-level effects of public hospital entry on private hospital counts. The results show that specialist public hospitals crowd in private entry, while non-specialist hospitals crowd out entry. Next, I study where within treated districts private hospitals choose to locate relative to the new public hospital.

Within the same district, private entrants already benefit from physician spillovers generated by a new public hospital. Given this shared labor pool, the spatial distribution of private entry reveals whether private hospitals view public hospitals as competitors or complements. If private hospitals view public hospitals primarily as competitors for patients, they should locate farther away to avoid direct price competition. Conversely, if they view public hospitals as complements that increase overall healthcare demand, they may choose to co-locate nearby.

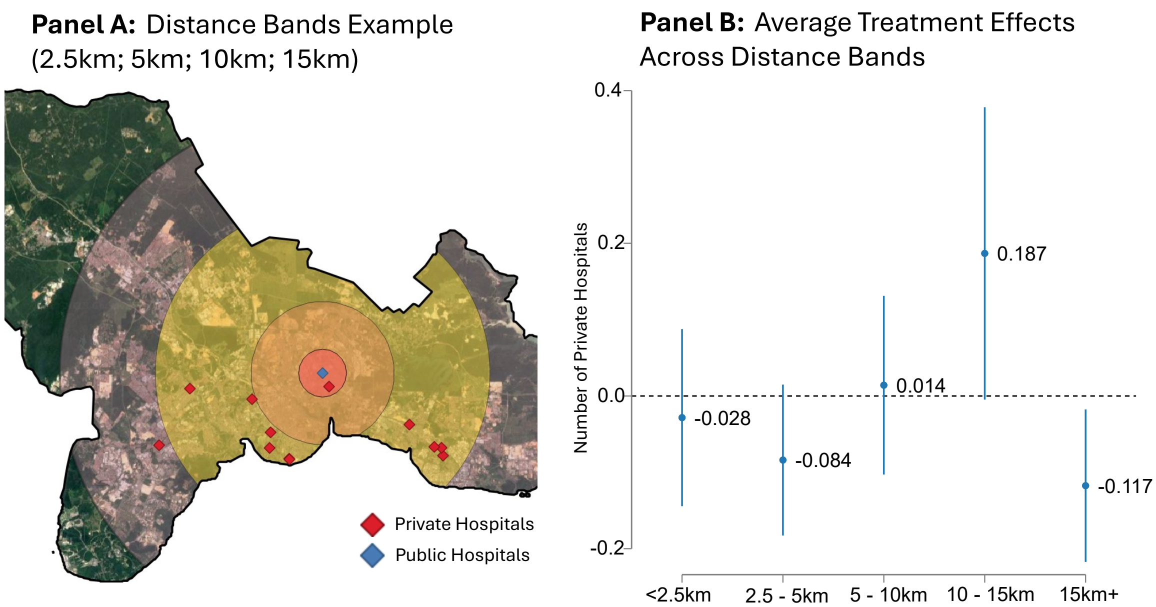
Additionally, private hospitals cannot locate too far from the public hospital without sacrificing access to the physician labor pool. Specialist physicians, who often work across both public and private facilities, would be unwilling to commute excessive distances between the two. This creates a tradeoff for private entrants between minimizing patient competition and maintaining proximity to shared medical staff.

To test this, I estimate the same event study specification in Equation 6, but with different outcome variables. Specifically, I count the number of private hospitals within certain distance bands from the newly constructed public hospital. Panel A of Figure 6 illustrates the treatment and control ring structure for a specific district. Panel B presents the average post-treatment effects across five distance bands.

The results show a nonlinear effect on private hospital entry. Within the immediate 2.5km vicinity of a new public hospital, private entry decreases slightly, though this effect is not statistically significant. However, entry declines sharply in the 2.5–5km band, with a statistically significant reduction of 0.084 hospitals. In contrast, private entry increases significantly in the 10–15km band, with 0.187 additional hospitals. Beyond 15km, the effect turns negative again, suggesting private hospitals avoid both the immediate competition zone and areas too distant from the physician labor pool.

These spatial responses align with both mechanisms identified earlier. District-level results show that specialist public hospitals crowd in private entry overall, which I interpret as public–private supply-side complementarities. The ring results show that, conditional on this district-wide supply channel, private entrants strategically position themselves to balance two competing forces: they avoid the immediate vicinity (2.5–10km) where patient competition is strongest, but concentrate in a zone (10–15km) where they can still access the shared physician pool while minimizing direct competition. The negative effects beyond 15km suggest that distances exceeding this threshold impose prohibitive commuting costs for dual-practicing specialist physicians.

Figure 6: Effects of Specialist Public Hospital on Private Entry Location



Notes: Panel A maps out an example of different distance band outcomes in the *Johor Bahru* district. The rings are 2.5km, 5km, 10km and 15km away from the newly constructed public hospital. Districts with multiple specialist public hospital constructed during this period are omitted from the sample. Panel B plots the post-treatment estimates using the Sun and Abraham (2021a) estimator across different distance bands. Each coefficient represents a separate regression estimate. The mean number of private hospitals are 0.29, 0.29, 1.43, 0.21, and 0.36 for distance bands 1 through 5, respectively. Standard errors clustered at the district level.

5.6 Impact of New Public Hospitals during Pre-1996 Privatization Period

The analysis above focuses on the post-1996 period after the Malaysian government committed to maintaining public healthcare provision. In this section, I examine the pre-1996 era when public hospitals faced significant corporatization policies to provide additional validation for the crowd-in mechanisms identified above.

The proposed corporatization policies involves maintaining the government as the main shareholder of hospitals, but operations would mirror that of private hospitals. Beginning with incremental reforms such as the corporatization of the largest public hospital (Hospital Kuala Lumpur)'s cardiac unit in 1992 and the contracting out of drug distribution systems in 1994. This policy uncertainty affected private hospitals, as incumbent private hospitals anticipate future competitors from newly corporatized public hospitals. For example, previously non-profit hospitals such as Lam Wah Yee Hospital re-registered to pursue profits during this period amidst such uncertainty (Barraclough, 2000).

Table 6 shows that during this earlier period, all types of public hospitals crowded out private hospital entry, with effects ranging from -0.035 for specialist hospitals to -0.095 for non-specialist hospitals. This uniform crowd-out pattern contrasts sharply with the post-1996 heterogeneous effects where specialist hospitals crowd-in private entrants.

One reason for explaining these reversals is the specialist physician training channel. The prospect of corporatization may allow specialist physician training in private hospitals, a significant shift given that such training was previously limited to public institutions. Additionally, public hospitals facing potential corporatization would pose a greater threat to private profits through funding structures combining government subsidies with profit-maximizing motives, leading to stronger direct competition with the private sector. The policy reversal came with the 7th Malaysia Plan (1996-2000), when the government recommitted to public healthcare provision and removed any notion of further corporatization policies.

Table 6: Effects of Public Hospital Entry on Private Hospitals: Pre-1996 Period

	Number of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	-0.084		
	(0.007)		
E2: Specialist public hospitals		-0.035	
		(0.019)	
E3: Non-specialist public hospitals			-0.095
			(0.009)
Mean Dep. Var.	0.166	0.204	0.181
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N Districts $\times$ Year	1,024	592	784
R^2	0.886	0.943	0.900
Unique Events	42	15	27
Estimator	SA	SA	SA

Notes: Each column presents results from separate regressions for the pre-1996 period when public hospitals faced corporatization/privatization pressures. Coefficient estimates are post-treamtent effects from the Sun and Abraham (2021) estimator. Standard errors in parentheses are clustered at the district level. The dependent variable is the number of private hospitals in a district. Column (1) includes all public hospitals; columns (2) and (3) separate by public hospital type.

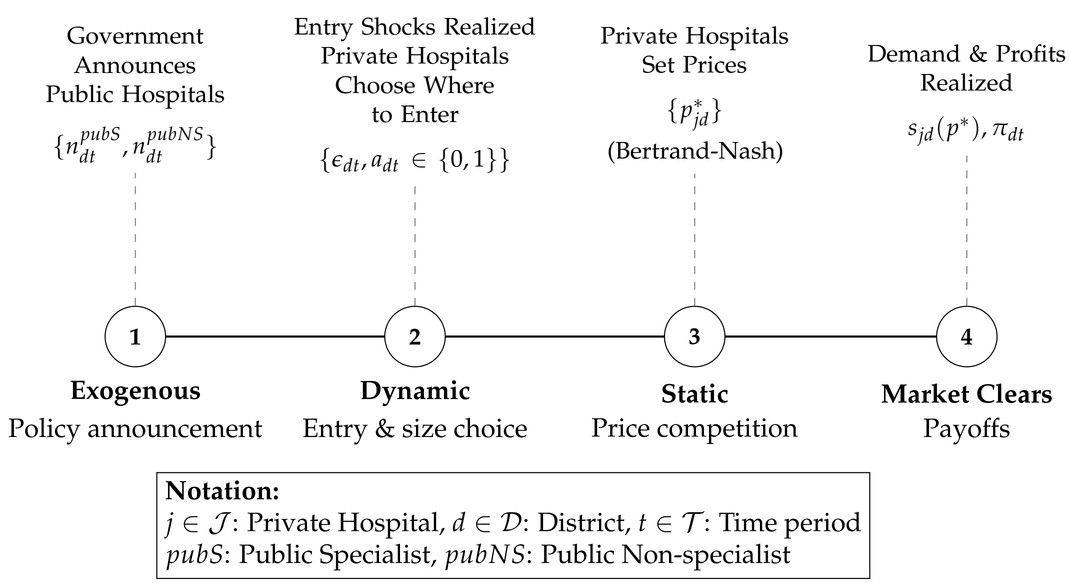
6 Structural Model and Estimation

6.1 Overview

The reduced-form findings show that specialist public hospitals crowd in private entrants by increasing the pool of specialist physicians within districts. In contrast, non-specialist public hospitals crowd out entrants by not providing sufficient complementarities to offset the competitive effects. However, these reduced-form estimates do not quantify how much the construction of a new public hospital reduces the entry costs of private hospitals to enter a market. In addition, the reduced-form estimates do not provide a framework to evaluate counterfactual policies where the government reallocates its budget across districts and hospital types to maximize welfare.

I estimate a model where private hospitals choose which districts (markets) enter. The decision to enter a market is inherently a forward-looking investment problem. Hospitals enter based on the expectation of a future stream of profits while weighing the costs of entry. This model of oligopolistic entry is in the spirit of Ericson and Pakes (1995) and Maskin and Tirole (1988).

Figure 7: Model Timeline



The timeline is summarized in Figure 7. First, the government announces where specialist and non-specialist public hospitals will be built, and private entrants perfectly observe this entire schedule. Second, each potential private entrant draws a specific idiosyncratic entry cost shock and decides whether to enter a district based on future profits, anticipated private specialist physician supply, population growth, and public hospital stocks. Third, after entry decisions are made, incumbent and new private hospitals engage in Bertrand price competition, taking public hospital prices as fixed at 100 MYR. Finally, consumer demand is realized through hospital choices, hospitals earn profits, and states evolve according to transition functions for physician supply and population.

This model section follows backward induction logic. I first estimate the second-stage demand system in Section 6.2, which determines hospital profits conditional on market structure. I then estimate the first-stage dynamic entry model in Section 6.3, which recovers entry costs using a simplified version of Bajari et al. (2007).

6.2 Second-Stage: Bertrand-Nash Equilibrium and Demand Estimation

I estimate demand using a random coefficients logit model by limiting to childbirth delivery services as I do not observe a full hospital demand system. Limiting specifically to birth deliveries has four benefits. First, births are the highest volume service in both public and private hospitals (See Table C.6 and Table C.5). Second, private hospitals in Malaysia offer maternity packages where mothers can choose between normal and caesarean section packages (See Figure C.3 for selected maternity promotional posters). This allows me to observe one price per hospital, where other conditions may be *ex-ante* unobservable to the consumers. I focus specifically on normal delivery, as caesarean section deliveries are less common and more likely to be influenced by individual medical circumstances. Private health insurance companies in Malaysia do not cover maternity packages, and patients pay out-of-pocket for these services. These demand estimates allow me to calculate hospital-specific total profits from childbirth deliveries, which I scale up based on the share of hospital admissions that are childbirth deliveries at a specific hospital.

Formally, consumer i choose between a set of hospitals and a maternity center option[8] j within district d for normal deliveries, and face an outside option of traditional health facilities or home births. The utility for consumer i choosing hospital j in district d is given by:

$$U_{ij} = \underbrace{\alpha_{g(i)}\, p_j}_{\substack{\text{Price}\\ \text{by}\\ \text{income}\\ \text{group}}} + \underbrace{\gamma_i\, \text{distance}_{ij}}_{\substack{\text{Travel}\\ \text{disutility}}} + \underbrace{\text{private}_j \cdot (Z_i'\mathbf{\Pi})}_{\substack{\text{Preference for}\\ \text{private hospitals}}} + \underbrace{H_j\beta}_{\substack{\text{Hospital}\\ \text{attributes}}} + \varepsilon_{ij}\,. \tag{8}$$

Where p_j is the price of hospital j and price sensitivity $\alpha_{g(i)}$ varies across income groups $g(i) = \{\text{low, mid, high}\}$. Public hospital prices are all subsidized and priced at MYR 100 or approximately 24 USD, while private hospital prices vary by hospital j. The term γ_i captures the disutility of travel distance to hospital j. distance_{ij} is the distance from consumer i to hospital j. The term private_j is an indicator for private hospitals. The effects

[8] I take the average characteristics of a maternity center wherever a district has a maternity center, and take the average price nationally. I do this as I do not have a full set of prices across all maternity centers

are captured by the coefficient vector Π which is interacted with consumer attributes Z_i to allow preferences for private care to vary across individuals. H_j is a vector of observed hospital characteristics which consist of congestion levels measured by bed occupancy rates[9] and a squared congestion term, total staff, number of medical subspecialties and a dummy for facility types. Facility types are either materniy centers, public specialist and non-specialist or private small (¡95 beds) or large ($\geq$ 95 beds) hospitals. The term ε_{ij} is an i.i.d. type-I extreme value error term. The utility of the outside option is normalized to zero : $U_{i0} = 0$.

I face several challenges in missing data and temporal misalignment in consolidating my demand estimation data. In 2013, there were a total of 134 private hospitals alongside 70 maternity centers, and 135 public hospitals. To construct my demand estimation data, I first drop hospitals that do not provide obstetrics services, this results in 122 private hospitals. Next, I drop private hospitals that did not have a maternity package during my primary data collection in 2013, which results in 105 private hospitals. Among these hospitals in my sample, 24 private hospitals and 12 public hospitals did not report birth deliveries in the inpatient admissions database, though they do report total inpatient admissions in 2013. For these hospitals, I assume that birth deliveries comprise 10.6 percent of total inpatient admissions for public hospitals and 5.9 percent for private hospitals, based on the mean proportion of deliveries observed among reporting hospitals (See Table C.6, Table C.5 and Figure C.2 for related distribution). I drop 18 private hospitals that did not report total inpatient admissions or birth deliveries in the electronic health records.

My final estimation sample includes 87 private hospitals out of an initial 135, after excluding facilities with missing survey agent data, zero reported prices, missing total inpatient admissions, or no obstetrics services. My final dataset includes 87 private hospitals, 19 districts with private maternity centers, 57 non-specialist public hospitals and 55 specialist public hospitals. This contrasts the data in 2013, where there were 123 private hospitals, 73 non-specialist public hospitals and 59 specialist public hospitals. The outside option share is obtained from the national survey of individuals that would seek hom or traditional births. To ensure that these data limitations do not bias my results, I provide a parsimonious version of my demand estimates by dropping hospitals that have missing prices or missing inpatient admissions, showing that the random coefficients logit model is comparable (see Table C.1 compared to Table C.3).

[9]Bed occupancy rates are calculated by dividing the total number of available bed-days over a year. For example, a hospital with 100 beds has 36,500 bed-days in a year (100 beds * 365 days). If the hospital had 25,000 inpatient days in that year, the bed occupancy rate would be 68.5 percent (25,000 / 36,500).

6.2.1 Estimation and Identification

I estimate the model using generalized method of moments (GMM) using the PyBLP python package (Conlon and Gortmaker, 2020, 2023). Further details of the demand estimation are in Appendix C. The estimation uses a set of moment conditions that relate the model's predicted market shares to the observed market shares and individual choices. Additionally, I match the share of consumers that choose private hospitals in district d varied by income groups and individual characteristics to the observed shares in the survey data.

To identify price sensitivity $\alpha(g_i)$, the standard concern is that prices may be correlated with unobserved hospital quality. While controlling for observed hospital characteristics H_j helps, I also use an instrumental variable approach. I construct a set of 'sums-of-characteristics' price instruments (Gandhi and Houde, 2019). For each hospital j, I compute the sum of observable characteristics of other hospitals operated by the firm (firms are categorized into the following groups: the government, solo entrepreneurship groups and hospital-chain groups) and those operated by competing firms. These instruments capture exogenous variation in hospital characteristics that shift price but are plausibly orthogonal to unobserved quality. The instruments are strong predictors of prices, and the first-stage F-statistic is 30.83.

The demand estimates are reasonable (See Table C.1). The preferred specification in Column (4) yields economically sensible parameter estimates that are consistent across model specifications. Price sensitivity decreases with income, distance deters private hospital choice, and hospital characteristics enter with expected signs. Consumers with private insurance favor private hospitals and those with chronic diseases are less likely to choose private hospitals. Comparing across the four specifications, micro moments are crucial for pinning down these heterogeneous preferences. This is shown by the contrast between imprecise estimates in Column (3) without microdata and the statistically significant coefficients in Column (4).

6.2.2 Hospital Profits and Expected Entry Profits

Given the demand estimates, I compute private hospital profits, markups, and marginal costs assuming Bertrand-Nash competition. I use the demand estimates from Column (4) of Table C.1 as my preferred specification. To align expected profits with 1996 entry decisions, I compute profits based on incumbent hospitals operating by 1996.

I recover hospital-specific marginal costs and profits from the first-order conditions of multi-product Bertrand pricing. Ownership groups include hospital chains (KPJ, Pantai, Columbia Asia, Sime Darby), solo entrepreneurship groups operating independent hospitals, and the government. Each ownership group f operates a portfolio of hospitals J_f within a district. The multi-product markup equation relates prices to marginal costs through the demand elasticity matrix: $p_j - c_j = -[\mathcal{H} \odot \mathbf{\Delta}^{-1}]_j$, where $\mathbf{\Delta}$ captures the matrix of cross-price derivatives $\frac{\partial s_k}{\partial p_j}$ between all hospitals, $\mathcal{H}$ is the ownership matrix (i.e., $\mathcal{H}_{jk} = 1$ if hospitals j and k are owned by the same firm), and $\odot$ denotes element-wise multiplication. Given my estimated demand parameters and observed prices, I invert this system to recover marginal costs c_j for each hospital, and then compute hospital-level profits as $\pi_j = (p_j - c_j)s_j M_d$, where s_j is hospital j's market share and M_d is the total number of births in district d. The distribution of these profits and markups are in Figure C.6.

To assess the external validity of my hospital profit estimates, I benchmark them against publicly available annual reports of major hospital groups. For KPJ Healthcare, their 2005 annual report indicates an average profit per hospital of approximately RM 2.3 million, which increased to RM 5.8 million by 2015. For IHH Holdings (the parent company of Pantai Hospitals), their 2015 annual report suggests a profit of roughly RM 16 million per hospital. My estimates for KPJ-owned hospitals (RM 8.0 million) and Pantai hospitals (RM 13.7 million) in 2015 are within a plausible range of these benchmarks. The conservative nature of my estimates potentially stem from limiting to only inpatient admissions, but does provide some credence to my profit calculations.

To construct expected entry profits for the dynamic model beginning in 1996, I face a temporal alignment challenge: my demand system is estimated using 2013 data, but I need profit expectations relevant to 1996 entry decisions. I therefore use the estimated demand elasticities to recover hospital-level margins, deflate prices and costs to 1996 MYR, and then restrict incumbents to facilities operating by 1996. Expected profits for a 1996 entrant are formed from the share-weighted mean profits of these 1996 incumbents (defined below), with a national-average benchmark for districts without 1996 private incumbents.

I compute expected profits from entering a district in the following steps. First, I scale hospital-specific birth delivery profits to total annual hospital profits using each hospital's ratio of birth deliveries to total admissions, which varies from 0.06 to 0.65 across facilities (See Figure C.2 for a density plot of the shares of birth deliveries as a proportion of all inpatient admissions). Second, I deflate 2013 prices and costs to 1996 nominal values using the national consumer price index, while keeping birth volumes at 2013 levels to isolate margin changes from demand growth.[10] Third, I aggregate these hospital-specific profits at the district level using only hospitals operating by 1996 (no type stratification).

For districts with at least one 1996 private hospital incumbent, I compute the market share-weighted mean incumbent profit:

$$\bar{\pi}^{SW}_{d,1996} \equiv \frac{\sum_{j \in I_d^{1996}} s_{jd,2013}\, \pi_{jd}^{1996}}{\sum_{j \in I_d^{1996}} s_{jd,2013}},$$

[10] Prices and costs are CPI-deflated to 1996; births are *not* backcast. The key variation comes from cross-district differences in market structure rather than temporal price trends.

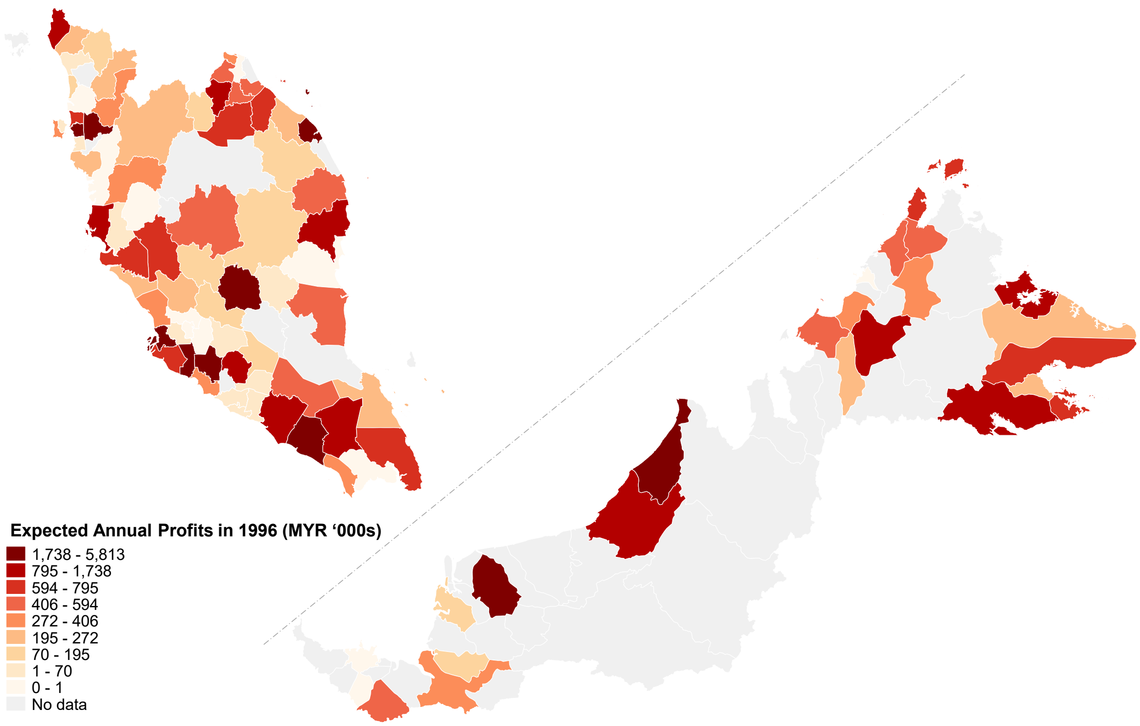
where $s_{jd,2013}$ are the demand shares used as weights and π_{jd}^{1996} are hospital-level profits deflated to 1996 MYR. I acknowledge that this share-weighted benchmark may not hold in principle. In reality, the private profit pool can increase or decrease depending on competitive responses. If private firms improve quality or services to attract patients away from public hospitals, the private profit pool may increase beyond what the static BLP profits predict. Conversely, if incumbent private hospitals respond to entry by reducing prices to maintain market share, or if public hospitals improve their quality in response to increased private competition, the private profit pool may decrease. Additionally, further entrants could intensify price competition and reduce the total profits available to private hospitals. For the dynamic entry model, I test this assumption by allowing market-level profits to vary above ($\gamma = 0.10$) or below ($\gamma = -0.10$) the baseline assumption, providing bounds on entry cost estimates under different competitive scenarios. Expected entrant profit is then:

$$\mathbb{E}[\pi_{d,1996}] = \bar{\pi}_{d,1996}^{SW}\,(1+\gamma),$$

where $\gamma \in \{-0.10, 0.00, 0.10\}$ is a term to capture robustness in expected profits while I set $\gamma = 0$ in the baseline case. For districts with no 1996 private incumbents, I construct a national-average synthetic entrant constructed from private-hospital national averages of market share, profit margins, and the births-to-admissions ratio to the district's birth market size to obtain expected profits for that district.

Figure 8 maps expected annual entrant profits (in thousands of 1996 MYR) under the baseline $\gamma = 0$ scenario. Profits concentrate in urban districts with larger populations, but there remains substantial cross-district variation, from near zero in rural districts to over 6 million MYR in the most profitable urban markets. The mean annual profits for an 'average' private hospital in 1996 is approximately 639 thousand MYR, with a standard deviation of 890 thousand MYR. This significant variation in expected profits across districts is crucial for identifying entry costs in the dynamic model, as hospitals weigh these profit opportunities against entry costs when making their entry decisions.

Figure 8: Expected Profits from Entering a District in 1996



Notes: Expected profits are computed at the district level under the baseline scenario ($\gamma = 0$). Hospital-level profits are estimated from the BLP demand model, scaled from birth-delivery profits to total hospital profits using facility-specific births-to-admissions ratios, and deflated to 1996 MYR. For districts with at least one 1996 private incumbent, expected entrant profit equals the *share-weighted mean* of incumbent profits in that district using BLP demand shares as weights. For districts without any 1996 private incumbents, a *national-average benchmark* (national average share, 1996 margin, and births-to-admissions ratio) is applied to the district's birth market size. Birth volumes are not backcast. Public hospital prices are fixed at MYR 100 in all calculations.

6.3 First-Stage: A Dynamic Model of Hospital Entry

6.3.1 Overview

Private hospital entry is a forward-looking investment decision where potential entrants weigh current entry costs against expected future profit streams. Hospitals anticipate how market conditions evolve over time as population grows, public hospitals open (bringing both physician supply increases and competitive pressures), and other private hospitals enter. I model entry decisions as a finite horizon dynamic discrete choice problem where private hospitals trade off immediate entry costs against expected future profits.

I estimate this model using a simplified version of Bajari et al. (2007), as my setting only involves entry decisions without exit[11] or investment decisions. A single potential entrant per district observes current market conditions and chooses whether to enter or wait for more favorable conditions over a 20-year planning horizon beginning in 1996.

The single-entrant restriction is empirically motivated as no district had multiple hospital entries within the same year during 1996-2013. Firms make entry decisions based on Markov-perfect equilibrium strategies, where strategies depend only on payoff-relevant state variables rather than the full history of play.

State Space and Entry Decision At each period t, a potential entrant in district d observes the current state S_{dt} and chooses an action $a_{dt} \in \{0, 1\}$ corresponding to 'wait' or 'enter'. The state vector captures all payoff-relevant information:

$$S_{dt} = \left(n_{dt}^{\text{pri}}, n_{dt}^{\text{pubS}}, n_{dt}^{\text{pubNS}}, \text{docs}_{dt}, \log(\text{pop}_{dt}) \right) \tag{9}$$

where n_{dt}^{pri} counts total private hospitals already operating, n_{dt}^{pubS} and n_{dt}^{pubNS} count specialist and non-specialist public hospitals, docs_{dt} measures private specialist physician supply, and $\log(\text{pop}_{dt})$ captures the log of district population.

Entry Costs Entry requires paying a one-time fixed cost that depends on local market conditions. I decompose entry costs into sunk costs (land acquisition, construction) and operational setup costs (recruiting the initial physician team). Entry costs are specified as:

$$C_{dt} = \underbrace{\beta_0 + \beta_1 \ln(\text{pop}_{dt}) + \beta_2 \text{LandPrice}_d}_{\text{Sunk Costs}} + \underbrace{\beta_3 \text{docs}_{dt}}_{\text{Operational Setup Costs}} + \delta_t + \epsilon_{jdt} \tag{10}$$

[11] Between 1996 and 2013, Malaysia's private hospital industry had zero exits. While there were some hospitals that were acquired or merged, these did not result in market exits. Additionally, some private hospitals also downsized or restructured without exiting the market. I do not observe these hospitals, and thus abstract away from this.

The coefficient β_1 captures how population growth increases land prices and construction costs, β_2 measures baseline land acquisition costs using district-level commercial land prices, and β_3 measures how specialist physician availability affects operational setup costs. The key hypothesis is $\beta_3 < 0$: more doctors reduce entry costs by lowering physician recruitment expenses and training requirements. Year fixed effects δ_t capture aggregate shocks (e.g., nationwide healthcare policy changes, macroeconomic conditions), and $\epsilon_{jdt} \sim$ T1EV$(0, 1)$ is an idiosyncratic cost shock that generates probabilistic entry decisions.

Expected Profits and the Bellman Equation Expected profits for entrants come from the BLP demand model estimated in Section 6.2. For each district d, I compute the expected per-period profit for a new private hospital entrant in 1996, denoted $\mathbb{E}[\pi_{d,1996}]$, using the baseline demand scenario ($\gamma = 0$) where public hospitals do not alter total private sector demand. This baseline profit serves as the anchor for computing profits in future periods as market conditions evolve. The value function for a potential entrant over a finite planning horizon of $T = 20$ years satisfies the finite horizon Bellman equation:

$$V(S_{dt}) = \mathbb{E}_\epsilon \left[\max \left\{V^{\text{wait}}(S_{dt}),\, V^{\text{enter}}(S_{dt})\right\}\right] \quad \text{for } t = 0, 1, \ldots, T-1 \tag{11}$$

where the choice-specific value functions are:

$$\begin{aligned} V^{\text{wait}}(S_{dt}) &= \beta \mathbb{E}[V(S_{d,t+1})] \quad \text{if } t < T \\ V^{\text{enter}}(S_{dt}) &= \sum_{\tau=0}^{T-1-t} \beta^\tau \mathbb{E}[\pi_{d,t+\tau} \mid S_{dt}] - C_{dt} \end{aligned} \tag{12}$$

with terminal condition $V(S_{d,T}) = 0$ for all terminal states. Per-period profits $\pi_{d,t+\tau}$ evolve from the baseline BLP estimate $\mathbb{E}[\pi_{d,1996}]$ according to the transition equation specified below.

State Transitions States evolve according to empirically estimated transition functions that combine deterministic and stochastic components. Private specialist physician supply follows an AR(1) process with discrete jumps when public hospitals open. I estimate the persistence parameter ρ_{doc} and district-specific fixed effects μ_d from a regression on the census data of 1980, 1991 and 2000:

$$\text{docs}_{d,t+1} = \alpha_d + \rho_{\text{doc}} \cdot \text{docs}_{dt} + u_{dt} \tag{13}$$

where α_d are district fixed effects and u_{dt} are residuals. This yields $\hat{\rho}_{\text{doc}} = 0.749$ (indicating high persistence in physician supply) and district-specific means $\hat{\mu}_d = \alpha_d/(1 - \rho_{\text{doc}})$ representing long-run doctor supply absent shocks. The standard deviation of residuals is $\hat{\sigma}_{\text{doc}} = 15.2$, which I use to calibrate the error draws in forward simulation. I then incorporate the causal effects of public hospital entry from the stacked two-way fixed effects estimates in Table 3. The full transition equation used in forward simulation is:

$$\text{docs}_{d,t+1} = \mu_d + \rho_{\text{doc}}(\text{docs}_{dt} - \mu_d) + \theta_S \mathbb{1}\{\text{new pubS}_{dt}\} + \theta_{NS} \mathbb{1}\{\text{new pubNS}_{dt}\} + \varepsilon^{\text{doc}}_{dt} \quad (14)$$

where $(\theta_S, \theta_{NS}) = (54.7, -6.0)$ are imposed from Table 3 and $\varepsilon^{\text{doc}}_{dt} \sim N(0, \sigma^2_{\text{doc}})$ with $\sigma_{\text{doc}} =$ 15.2. This specification directly links the structural model to the reduced-form evidence: each new specialist public hospital increases private doctor supply by 54.7 physicians on average, which then feeds into entry costs through the β_3 coefficient in equation (10). Population follows a similar AR(1) process, estimated from the panel:

$$\log(\text{pop}_{d,t+1}) = (1 - \rho_{\text{pop}})\mu^{\text{pop}}_d + \rho_{\text{pop}} \log(\text{pop}_{dt}) + \varepsilon^{\text{pop}}_{dt} \quad (15)$$

where $\hat{\rho}_{\text{pop}} = 0.875$ governs persistence, μ^{pop}_d is the district-specific long-run mean log population (estimated from district fixed effects), and $\varepsilon^{\text{pop}}_{dt} \sim N(0, \sigma^2_{\text{pop}})$ with $\hat{\sigma}_{\text{pop}} = 0.048$. This mean-reverting process captures that population growth rates converge toward district-specific trends rather than diverging indefinitely. Public hospital state transitions follows the deterministic schedule announced by the Ministry of Health through 2013:

$$n^{\text{pubS}}_{d,t+1} = n^{\text{pubS}}_{dt} + \mathbb{1}\{\text{new pubS}_{dt}\} \quad (16)$$

$$n^{\text{pubNS}}_{d,t+1} = n^{\text{pubNS}}_{dt} + \mathbb{1}\{\text{new pubNS}_{dt}\} \quad (17)$$

This deterministic structure reflects the centralized planning process described in Section 2 where public hospital locations and timing are determined by five-year development plans. I observe this schedule through 2013 and assume no new public hospitals open thereafter.

Profit Evolution Post-Entry Once a hospital enters, its per-period profit evolves with market conditions. Let $\mathbb{E}[\pi_{d,1996}]$ denote the expected baseline profit from the BLP demand model for a new entrant in district d in 1996. Realized profits in subsequent periods adjust for demand growth and public hospital crowd-out:

$$\pi_{dt} = \pi_0 \times \underbrace{\frac{\text{pop}_{dt}}{\text{pop}_0}}_{\text{Demand Growth}} \times \underbrace{\left(1 - \delta_S \times \mathbb{1}\{n^{\text{pubS}}_{dt} > 0\}\right) \times \left(1 - \delta_{NS} \times \mathbb{1}\{n^{\text{pubNS}}_{dt} > 0\}\right)}_{\text{Public Crowd-Out}} \quad (18)$$

where the public crowd-out parameters are $\delta_S = 0.698$ for specialist hospitals and $\delta_{NS} =$ 0.379 for non-specialist hospitals, obtained directly from the reduced-form estimates in

Table 3. The first term captures demand expansion from population growth, holding the competitive structure fixed at its 1996 baseline. The second term captures the demand crowd-out effect when public hospitals enter the market, drawing patients away from private hospitals. This formulation captures competing complementarities: public hospitals reduce entry costs through physician spillovers ($\theta_S = 54.7$ in equation (14)) but decrease post-entry profits through demand crowd-out. The net effect on private entry depends on which channel dominates.

6.3.2 Estimation Strategy: Two-Step BBL Approach

I estimate the model using the Bajari et al. (2007) two-step approach, which avoids solving the full dynamic programming problem by first recovering conditional choice probabilities (CCPs) from observed entry decisions, then using forward simulation to compute value functions. This method is particularly suitable for my setting for three reasons. First, I only observe entry decisions (not investments or exits), simplifying the action space. Second, the Type I Extreme Value distribution assumption on cost shocks yields closed-form logit choice probabilities. Finally the linear cost function in equation Equation 10 combined with the Hotz-Miller inversion allows direct recovery of cost parameters from a simple regression rather than a set of moment inequalities.

Step 1: Policy Function Estimation I estimate entry probabilities using a binary logit model on observed entry decisions across 92 districts over 1996-2012 (1,564 district-year observations):

$$\ln\left(\frac{P(\text{enter} \mid S_{dt})}{P(\text{wait} \mid S_{dt})}\right) = \beta_0 + \sum_{j=1}^{4} \beta_j \mathbb{1}\{\text{doc bin}_j\} + \beta_2 n_{dt}^{\text{pubS}} + \beta_3 n_{dt}^{\text{pubNS}} + \beta_4 n_{dt}^{\text{pri}} + \beta_5 \log(\text{pop}_{dt}) \tag{19}$$

Doctor supply enters flexibly through quintile bin dummies (with a separate bin for zero doctors) to capture potential non-linearities. I include the stock of private hospitals n_{dt}^{pri} to control for competition effects, and public hospital stocks to account for how existing public capacity affects entry incentives. Standard errors are clustered at the district level. The estimates are in Table C.4. The estimates align with the reduced form findings. Private hospitals are more likely to enter into areas with private specialist physicians, though the effect is non-monotonic. With the stock of private specialist physicians controlled for, private entrants are less likely to enter markets with more public specialist or non-specialist hospitals, or private hospitals. Larger populations also increase entry probabilities.

Step 2: Finite Horizon Forward Simulation For each initial state $(d, t = 1996)$, I simulate $R = 500$ forward paths over $T = 20$ periods (1996-2015) under two policy scenarios: (i) enter immediately at $t = 0$, and (ii) follow the estimated CCP policy ('wait'). For each simulation path, I draw stochastic shocks for doctor supply and population transitions according to equations (14) and (15), implement the observed public hospital schedule through 2013, and compute period-specific profits using equation (18), which evolves the BLP baseline profit $\mathbb{E}[\pi_{d,1996}]$ forward according to market conditions.

For the 'wait' policy, I implement optimal stopping: at each period before entry occurs, the firm draws an entry decision from the estimated CCP $P(\text{enter} \mid S_{dt})$. If 'wait' is chosen, the simulation continues; if 'enter' is chosen, the firm enters immediately and begins earning profits for the remainder of the horizon. For competing entrants, I model their decisions using the same estimated CCPs, assuming they act as a competitive fringe. At each period, with probability $P(\text{enter} \mid S_{dt})$, another private hospital enters the market, increasing competition.

I set the continuation value to zero at the terminal period: $V(S_{d,T}) = 0$ for all terminal states, regardless of whether entry has occurred. This finite horizon specification focuses identification on the 1996-2015 window when public hospital construction created exogenous variation in physician supply. Given the discount factor $\beta = 0.95$, the present value weight on periods beyond year 20 is only $\beta^{20} = 0.36$, and the primary policy-driven variation occurs during 1996-2013. The total discounted value for each path is $\sum_{t=0}^{T-1} \beta^t \pi_{d,1996+t}$. Where $\pi_{d,1996+t}$ equals zero before entry occurs and follows equation (18) after entry, evolving from the BLP baseline $\mathbb{E}[\pi_{d,1996}]$ according to population growth and public hospital crowd-out effects. I average across the $R = 500$ paths to obtain $V^{\text{wait}}(S_{d,1996})$ and $V^{\text{enter}}(S_{d,1996})$ for each initial 1996 state.

Recovering Choice-Specific Value Functions The Type I Extreme Value distribution of cost shocks yields the Hotz-Miller inversion (Hotz and Miller, 1993), which directly relates choice probabilities to value differences:

$$V^{\text{enter}}(S_{dt}) - V^{\text{wait}}(S_{dt}) = C_{dt} + \ln\left(\frac{P(\text{enter})}{P(\text{wait})}\right) \tag{20}$$

Let $\Delta W_{dt} = V^{\text{enter}}(S_{dt}) - V^{\text{wait}}(S_{dt})$ denote the value difference from forward simulation and $\eta_{dt} = \ln(P(\text{enter})/P(\text{wait}))$ the estimated log-odds. Rearranging gives:

$$\kappa_{dt} \equiv \Delta W_{dt} - \eta_{dt} = C_{dt} \tag{21}$$

which represents the revealed entry cost. The intuition is straightforward: κ measures the cost burden needed to reconcile the simulated value difference ΔW with the observed entry probability (through η).

Second-Stage Regression Substituting the cost function from equation (10) into equation (21) yields the second-stage regression:

$$\kappa_{dt} = \beta_0 + \beta_1 \ln(\text{pop}_{dt}) + \beta_2 \text{LandPrice}_d + \beta_3 \text{docs}_{dt} + \delta_t + u_{dt} \tag{22}$$

I estimate this using OLS with year fixed effects δ_t and standard errors clustered at the district level. The key parameter is β_3, which measures how private doctor supply affects operational entry costs. The hypothesis is $\beta_3 < 0$: more doctors reduce entry costs. When specialist public hospitals increase doctor supply by $\theta_S = 54.7$, operational entry costs fall by approximately $-\beta_3 \times 54.7$ thousand MYR. One threat to identification is reverse causality, as districts with higher unobserved entry potential may attract more doctors. I address this using lagged doctor supply from the 1980 census as an instrument. This instrument satisfies relevance (historical physician stocks predict contemporary supply) and plausibly satisfies exclusion (1980 doctor counts affect 1996-2012 entry decisions only through 1996 doctor supply). However, the instrument suffers from weak identification (first-stage $F = 5.0$). Consequently, I report both OLS and IV estimates, interpreting OLS as conservative given likely attenuation bias from measurement error.

6.4 Results

Figure 9 plots the estimated total entry costs by districts in 1996 for an 'average' private entrant. Estimated mean entry costs are approximately 6 million MYR, while mean annual profits are approximately 639 thousand MYR. This implies that a private hospital would need to operate for close to a decade to recoup its entry costs, assuming no changes in the market structure or profits.

Table 7 presents the second-stage cost estimates from the finite horizon model. Column 1 shows the OLS estimates of the second-stage estimation. Entry costs average RM 6.54 million and decrease with physician supply. The coefficient implies that each additional physician reduces entry costs by RM 23,050. Specialist public hospitals, which increase local physician supply by 54.7 doctors on average (Table 3), therefore reduce private hospital entry costs by approximately RM 1.26 million. This amounts to a 19.3 percent reduction in mean entry costs. Column 2 presents the instrumental variables estimates. The IV coefficient is -25.88, showing the same sign and a similar magnitude to OLS. The consistency across both specifications suggests that endogeneity concerns may not be driving the results.

Given that specialist public hospitals have mean market shares of 55 percent in their districts in 2013, this implies that public hospitals compete away a large share of the hospital market but also facilitates private sector entry by lowering entry costs through physician spillovers.

Figure 9: Second-Stage BBL Cost Estimates Across Districts in 1996

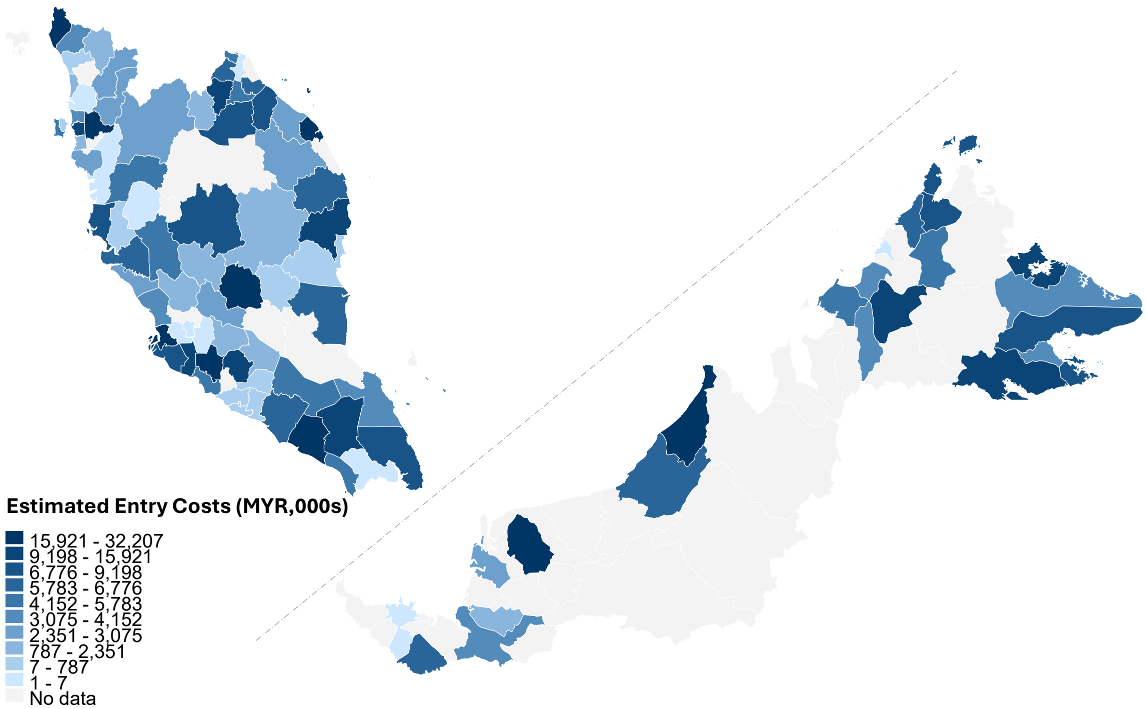


Table 7: Entry Cost Estimates with Varying Profit Expectations (γ)

	Baseline ($\gamma = 0$)		**Scenario A** ($\uparrow \mathbb{E}[\pi_{dt}]$) ($\gamma = 0.1$)		**Scenario C** ($\downarrow \mathbb{E}[\pi_{dt}]$) ($\gamma = -0.1$)	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Private doctors (1996)	-23.05	-25.88	-24.25	-28.11	-20.31	-22.77
	(11.63)	(14.16)	(13.07)	(15.49)	(10.53)	(12.69)
Log population	2292.40	2459.09	2515.14	2742.32	2044.76	2189.81
	(1338.74)	(1419.02)	(1468.73)	(1571.86)	(1199.82)	(1274.31)
Land price (RM/sqft)	0.44	0.45	0.48	0.49	0.38	0.39
	(0.43)	(0.44)	(0.47)	(0.48)	(0.38)	(0.39)
Observations	94	94	94	94	94	94
R^2	0.07	0.07	0.07	0.07	0.07	0.07
Implied effect of specialist public hospital:						
Mean entry cost (RM 000s)	6,535		7,188		5,868	
Cost reduction (RM 000s)	1,261	1,416	1,326	1,538	1,111	1,246
As % of mean cost	19.3%	21.7%	18.5%	21.4%	18.9%	21.2%

Notes: Dependent variable is the revealed entry cost κ. Columns vary the parameter γ, which adjusts how firms weigh future expected profits. Standard errors are in parentheses. Mean entry cost is the mean of the dependent variable from summary statistics corresponding to each γ specification. Cost reduction is calculated as $-$(private doctors coeff) $\times$ 54.7 thousand MYR, where 54.7 is the specialist hospital effect on physician supply from Table 3.

7 Conclusion

This paper studies how new public hospitals affect private hospital entry in Malaysia using a staggered event study design. The main results show that specialist public hospitals significantly crowd-in private hospital entry (0.785 additional hospitals on average), while non-specialist public hospitals crowd-out private entry (-0.171 hospitals). The structural model quantifies these effects, showing that new specialist public hospitals reduce fixed private entry operational costs by approximately 44 percent. The central contribution of this paper is in showing the tension of public provision in crowding-in or crowding-out private investment conditional on its competition and complementarities with the private sector. When public provision generates sufficient complementarities with private firms through labor spillovers, this can stimulate rather than displace private investment. This tension is important to understand and quantify as it determines whether public spending stimulates local economic activity or merely substitutes for private provision.

These findings demonstrate that public provision can be thought of as a policy tool beyond just improving equity. Public provision can strategically affect market structure and has significant implications for welfare and economic development. In this specific context of hospital markets, my findings show that specialist physicians are the key inputs driving entry decisions, and because the public sector controls physician training infrastructure, specialist public hospitals crowd-in private investment through labor market complementarities. Public hospitals also exert competitive pressures on private entrants, and this directly affects private hospital consumers.

Overall, this paper highlights the importance to account for private sector responses when making public spending and provision decisions. A similar idea is shown in Andrabi et al. (2024), which shows that improving public school quality in Pakistan can lead to a multiplier effect from private investment in improving private quality. These findings are particularly important for policymaking in developing countries where healthcare providers consist of both public and private actors, with physicians often working in both sectors and where public hospitals serve as the primary training ground for medical professionals. Given the rapid expansion of both public and private healthcare systems in many developing countries, understanding these interactions can make public interventions more targeted to local contexts and needs. Depending on whether private investment is desired, specialist hospitals can play a strategic role in stimulating complementary private investment while achieving public health objectives.

There are several important limitations of this paper which suggest important avenues for future research. This paper does not examine quality differences between public and private hospitals, which matter for healthcare services and patient outcomes. While I show that specialist public hospitals increase private physician supply, the welfare implications of physician migration from public to private practice remain unclear. Such reallocation may improve efficiency through better matching of skills to patient needs, or it may exacerbate healthcare inequality if it reduces access to specialized care in the public sector. Future work on the equilibrium effects of public-private competition on health care quality is a fruitful avenue for exploration.

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A Details on Data and Context

A.1 Hospital Panel Data Details

I have data on four years of the National Healthcare Establishment and Workforce Survey (NHEWS) (2010-2013) by the Clinical Research Centre. This survey provides me with a panel dataset of hospitals, whether the hospital provides certain services, the year in which hospitals began providing services, and year-specific levels of admission, congestion.

The survey is an initiative that gathers information on hospitals in the country concerning their services- with emphasis on specialized clinical services, facilities, medical devices, and health workforce. The NHEWS survey covers all acute curative hospitals and related specialty services for both public and private sectors. This survey asks all facilities that provide inpatient admissions in Malaysia. The survey respondent is the person-in-charge for the administrative department of hospitals. Response rates for public hospitals is 100 percent but for private hospitals it is 83.6 percent for those with less than 20 medical subspecialties and close to 90 percent for those with more than 20 medical subspecialties.

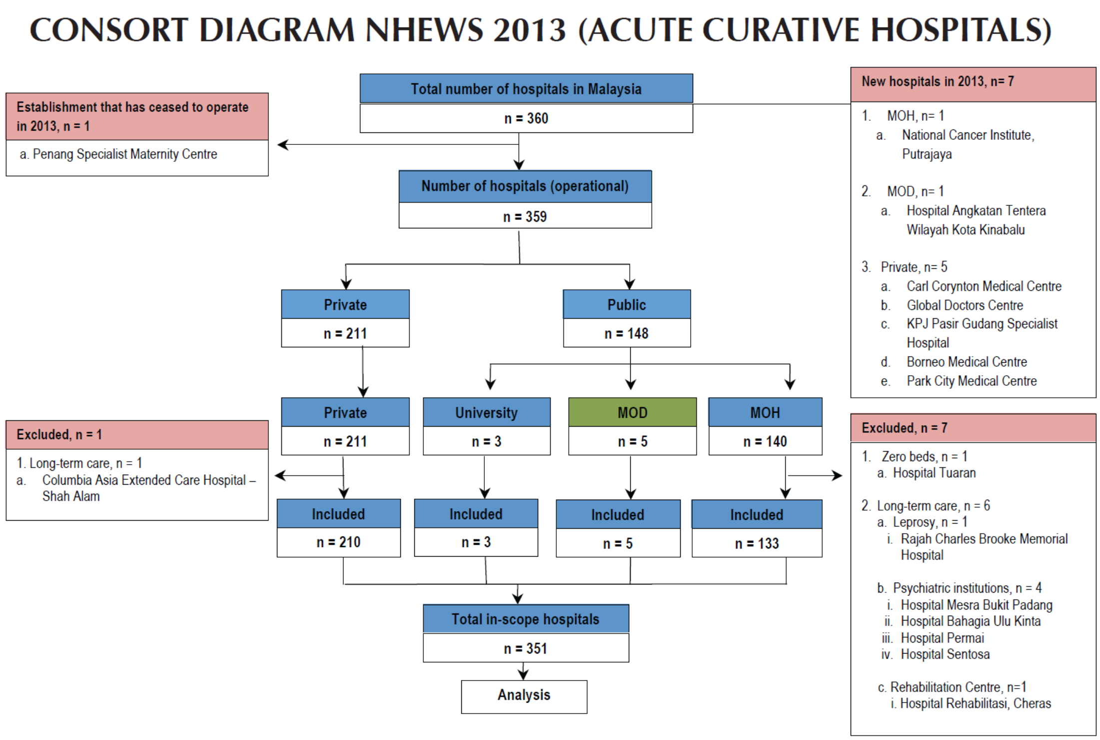
Respondents had the option between two modes of data collection and submission:

1. Paper data submission via hard copy case report forms (printed CRF)
2. Electronic data submission via National Healthcare Statistics Initiative web application electronic case report forms (eCRF)

Data collection for the workforce section, particularly for the doctor workforce involved relevant details (e.g. qualification and specialty) of each doctor working in the hospital. Datasets containing the list of doctors for each hospital, which was obtained from its participation in the past NHEWS (Hospital) surveys, were pre-uploaded to the eCRFs of 2013. This aimed at minimizing the need for manual data entry of the current survey. In comparison, data obtained for the remaining workforce category involved only the total count of the workforce.

Data from paper submissions were screened manually and reviewed for their completeness and logical consistency before data entry into the NHEWS (Hospital) database by trained members. Data submissions through electronic CRFs were entered directly into the NHEWS (Hospital) database by the data providers. Quality of data entry was inspected and maintained by several built-in features such as a compulsory data checking, consistency checks, auto-calculations and auto-default data from the previous NHEWS (Hospital) surveys. Activities performed in the database were recorded by an audit trail system.

Figure A.1: Sample Details for NHEWS (2010-2013)



Notes: This figure presents sample details from the National Healthcare Establishment and Workforce Survey (NHEWS) in 2013.

A.2 Additional Survey Data Details

The National Health and Morbidity Survey is a nationally representative, two-stage (states and urban-rural status) stratified randomly sampled household survey in Malaysia. My final sample consists of respondents aged 18 and above who responded yes to the enumerator about their desire of having a child. The survey asks respondents on hypothetical choice scenarios for birth deliveries after sociodemographic questions. Specifically, the question asks:

"Which is the main health facility you would go to in the following situations?" "For birth delivery, where would you go?".

The respondent could choose exactly one from four possible responses: "government", "private", "traditional/complementary/alternative health facility" and "will not go to any facility". I chose to omit the fourth option–will not go to any facility–as the percentage of individuals answering this option is less than 0.5 percent. Following the hypothetical choice questions, the survey asks individuals on their perception of quality. The survey question asks the respondent on ratings on a 1 to 5 Likert scale, which encompasses 12 different questions of quality for outpatient care and inpatient care, in both the public and the private sector. I specifically use the questions *'Based on your perception or impression, how would you rate the government and private hospital on the following aspect ...'*. First, *'The waiting time to see a doctor once arrived at a hospital'* followed by *'Your overall impression'* Answers do not correspond to specific types of health conditions, and instead refers generally to the public and private sector.

Figure A.2: Quality Perception Survey Questionnaire

Sangat tidak bagus *Very Poor*	Tidak bagus *Poor*	Sederhana *Fair*	Bagus *Good*	Sangat bagus *Excellent*
1	2	3	4	5

(-7) TT (-9) EJ

Berdasarkan tanggapan atau kepercayaan anda [kepada penemuramah: sekiranya responden menghadapi masalah, anda boleh bantu dengan mencadangkan, e.g. Daripada perkhabaran/pengalaman keluarga, rakan-rakan anda, pengalaman anda sendiri], bagaimana anda menilai **HOSPITAL** kerajaan dan swasta (pesakit dalam) pada aspek berikut ... / *Based on your perception or impression [to interviewer: if respondent has trouble answering, you can help them by suggesting, e.g. What you hear from your relatives and friends, other's experience, own experience], how would you rate the government and private* ***HOSPITAL*** *(inpatient) on the following aspect …*

Tanya semua soalan berkenaan fasiliti Kerajaan dahulu, diikuti dengan Swasta.

		Hospital / *Hospital*	
		Kerajaan *Government*	Swasta *Private*
AC215	Kesesuaian lokasi hospital *Convenience of hospital location*		
AC216	Boleh memohon bilik persendirian / tidak berkongsi dengan ramai pesakit lain / *Ability to ask for a private room / sharing with less people*		
AC217	Keselesaan hospital (cth: kebersihan, susun atur kerusi, ruang, dll.) / *Comfort of hospital (e.g. cleanliness, setting of chairs, space, etc.)*		
AC218	Adanya ujian/ peralatan perubatan *Availability of investigations/ medical equipment*		
AC219	Adanya doktor pakar di hospital pakar *Availability of specialist (s) at the specialist hospital*		
AC220	Dibenarkan memilih doktor *Allowed to choose the doctor*		
AC221	Tempoh menunggu untuk berjumpa doktor sebaik tiba di hospital *The waiting time to see a doctor once arrived at the hospital*		
AC222	Masa yang diluangkan oleh doktor untuk pesakit *The amount of time the doctor spends with a patient*		
AC223	Kebolehan doktor memberi diagnosis dan memberi rawatan yang betul / *The ability of the doctor to give you the correct diagnosis and treatment*		
AC224	Kejelasan penerangan doktor berkenaan penyakit, ujian dan prosedur / *Clarity of doctor's explanation regarding the illness, test and procedure*		
AC225	Budi bahasa dan kesediaan doktor, penolong pegawai perubatan & jururawat untuk membantu / *Courtesy and helpfulness of doctor, assistant medical officer and nurse*		
AC226	Keberkesanan perkhidmatan / rawatan *The outcome of services / treatment*		
AC227	Caj rawatan *Treatment charges*		
AC228	Pandangan anda secara keseluruhan *Your overall impression*		

Note: This figure shows the questions asked in the National Health and Morbidity Survey (NHMS) on quality perception for hospital services.

A.3 Additional Tables and Figures on Data and Context

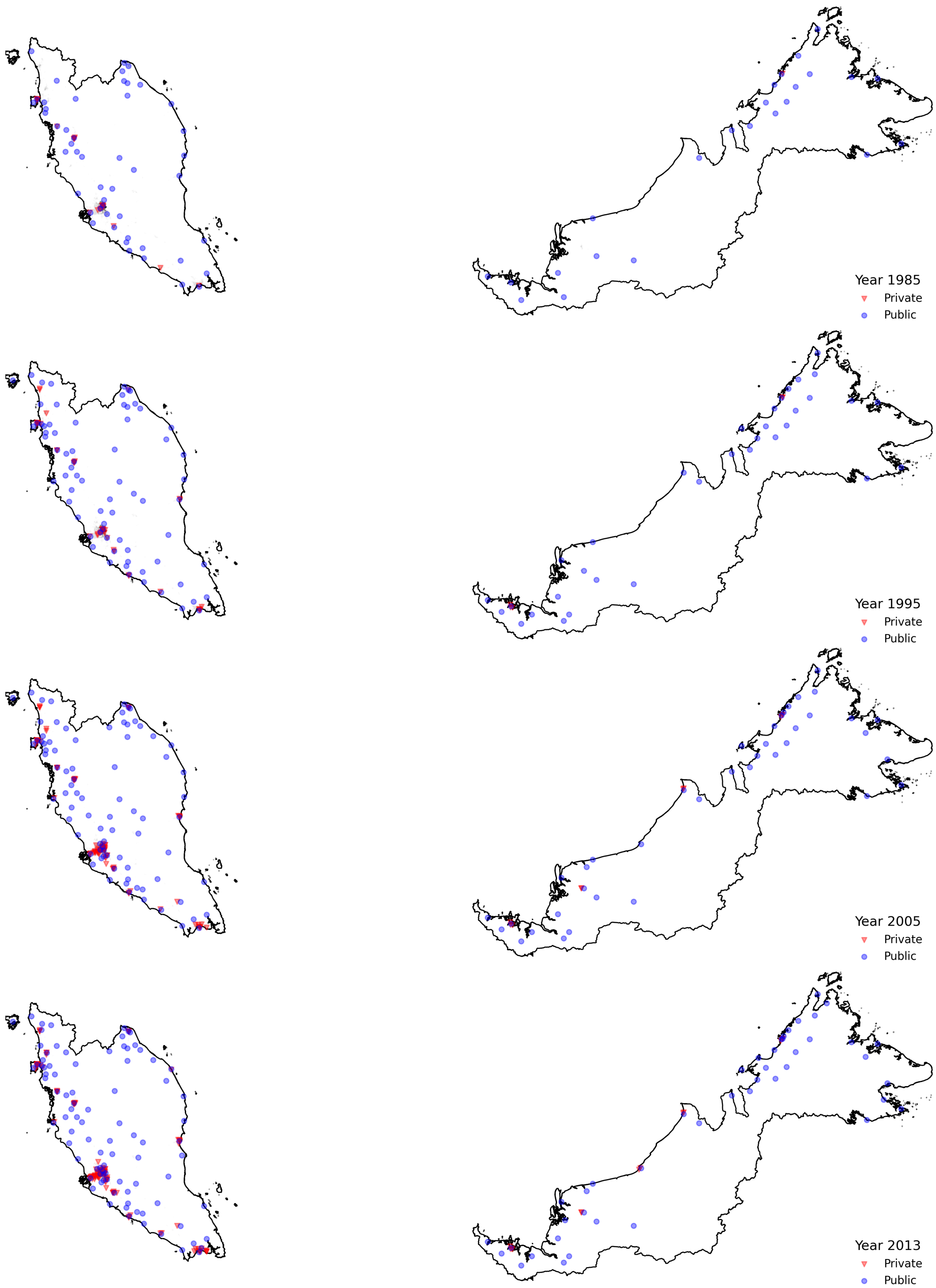
Table A.1: Summary Statistics

	Public Hospitals Specialist	Public Hospitals Non-Specialist	Private Hospitals
A. Hospital Characteristics (2013)			
N Hospitals	61	74	134
Avg. Physician	226.39	12.36	34.89
Avg. Other Staff	719.79	80.91	133.29
Avg. Beds	509.08	88.80	94.06
Avg. Inpatient Admissions	34,291	5,432	8,395
Avg. Outpatient Visits	96,276	52,539	28,116
Avg. Bed Occupancy Rate (%)	73.9	47.33	53.88
Ownership Group (%)			
Government	61 (100%)	74 (100%)	-
Independent	-	-	87 (65%)
Columbia Asia	-	-	11 (8%)
KPJ	-	-	22 (16%)
Pantai	-	-	11 (8%)
Sime Darby	-	-	3 (2%)
B. Maternity Services			
Avg. Vaginal Deliveries	3,176	586	589
Avg. District Market Share (Deliveries)	0.70	0.79	0.08
Price (MYR)	100	100	3,306

	Survey Data: Public Hospitals	Survey Data: Private Hospitals
C. Survey Data		
Indv. Monthly Income (MYR)	1.52	2.54
Distance Public (km)	13.17	10.28
Distance Private (km)	31.82	15.31
Private Insurance	0.16	0.52
Chronic Disease	0.70	0.61
Quality Rating (1-5)	4.03	3.83
Wait Time Satisfaction	3.23	3.82

Notes: Panel A shows characteristics for 269 hospitals from the National Healthcare Establishment and Workforce Survey (NHEWS). Panel B presents maternity service statistics for normal vaginal deliveries from Ministry of Health electronic health records (SMRP for public, PHDD for private hospitals). Public hospital prices reflect standardized subsidized rates for third-class wards. Private hospital prices are minimum advertised rates from primary data collection (websites, social media, direct contact). Panel C shows stated preferences from 15,296 families with childbearing intentions in the National Health and Morbidity Survey (NHMS) 2015, split by hospital type preference. Distance measured as straight-line distance from households to nearest hospital within each district. Income in thousands of MYR. Quality rating and wait time satisfaction on 1-5 Likert scales.

Figure A.3: Public and Private Hospital Locations (1982-2013)

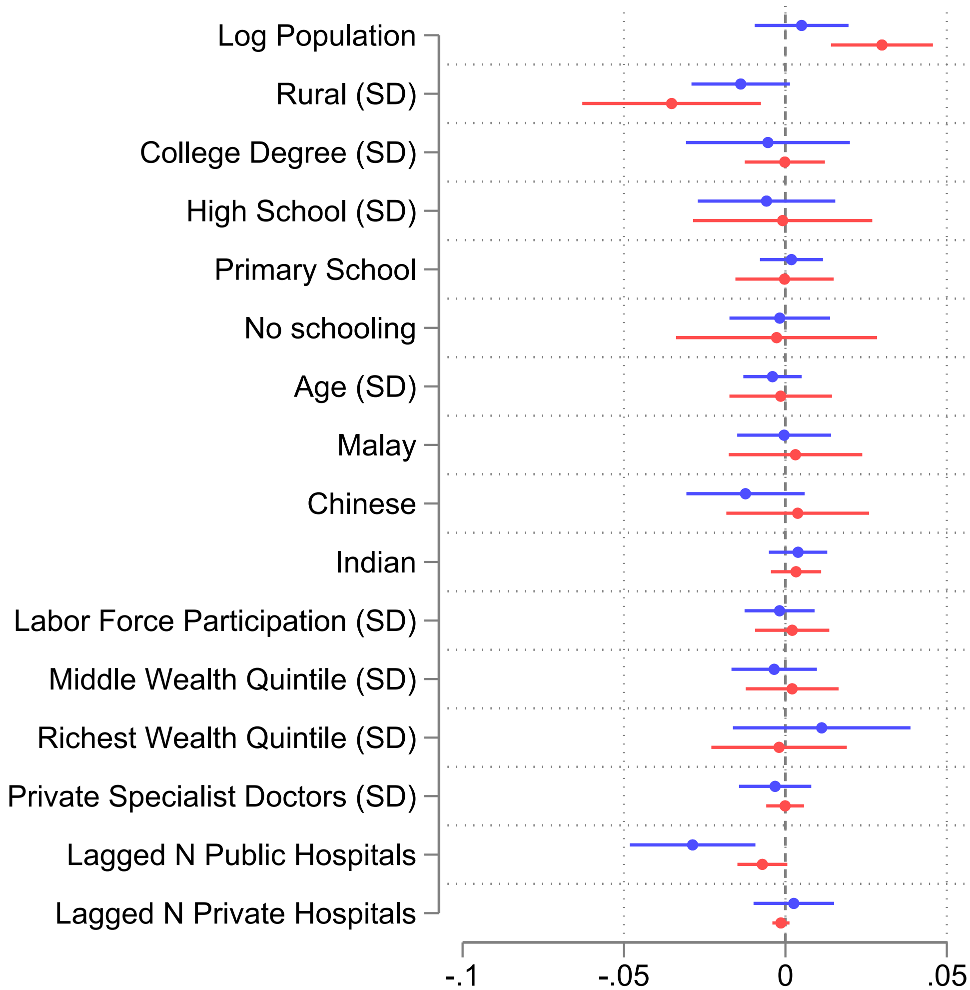


Note: Data on hospital locations are from the National Healthcare Establishment Workforce Survey (2013). This figure shows the locations of public and private hospitals in Malaysia from 1982 to 2013.

Figure A.4: Example Hospital Images

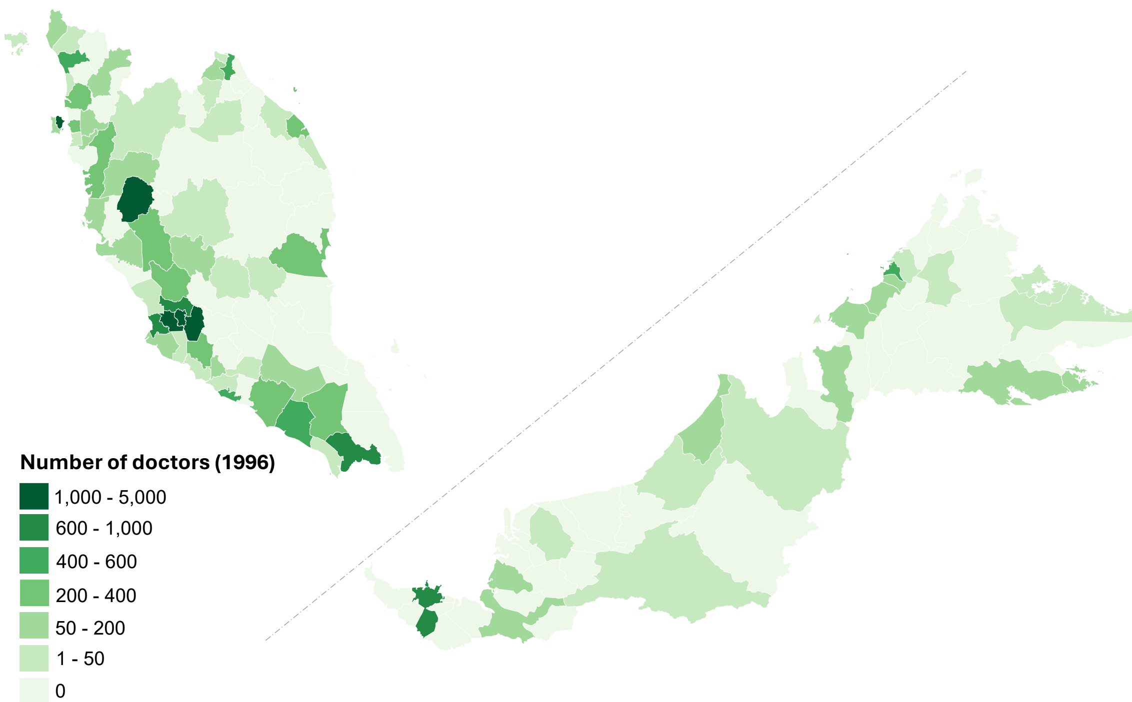
Note: These panels show examples of what hospitals in Malaysia look like based on their categories.

Figure A.5: Determinants of Public and Private Hospital Entry (Full Coefficient Set)



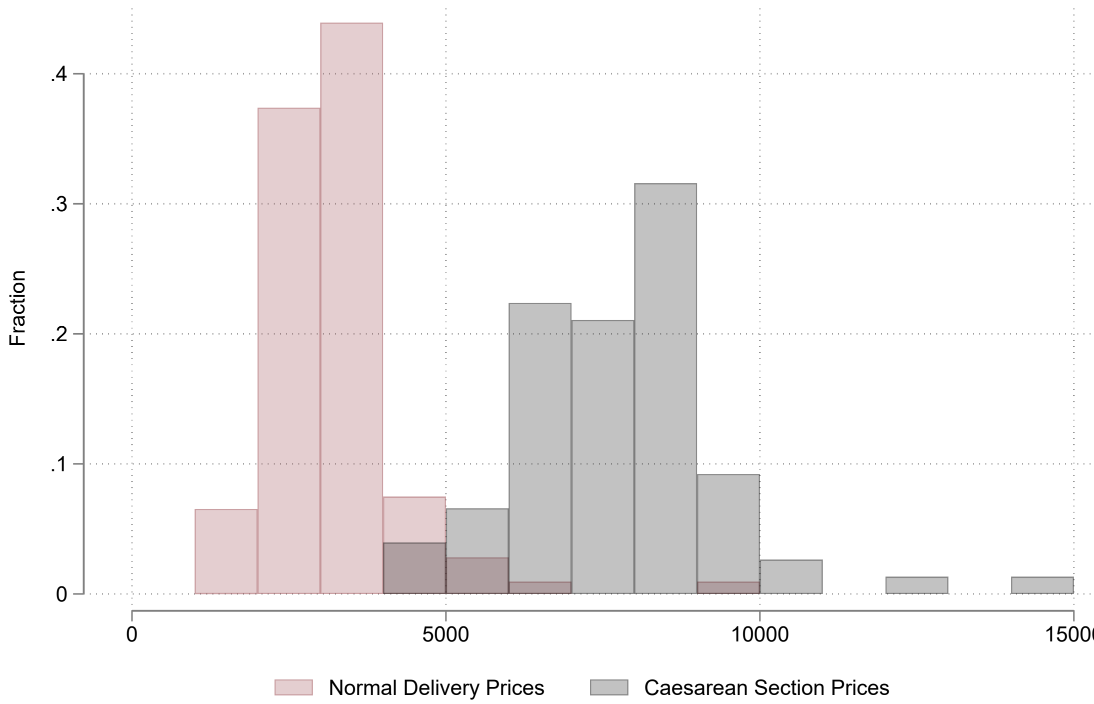
Note: These coefficients are average marginal effects from logit regressions with year fixed effects of public (or private) hospital entry on a set of district characteristics.

Figure A.6: Number of Doctors Across Districts (2000)



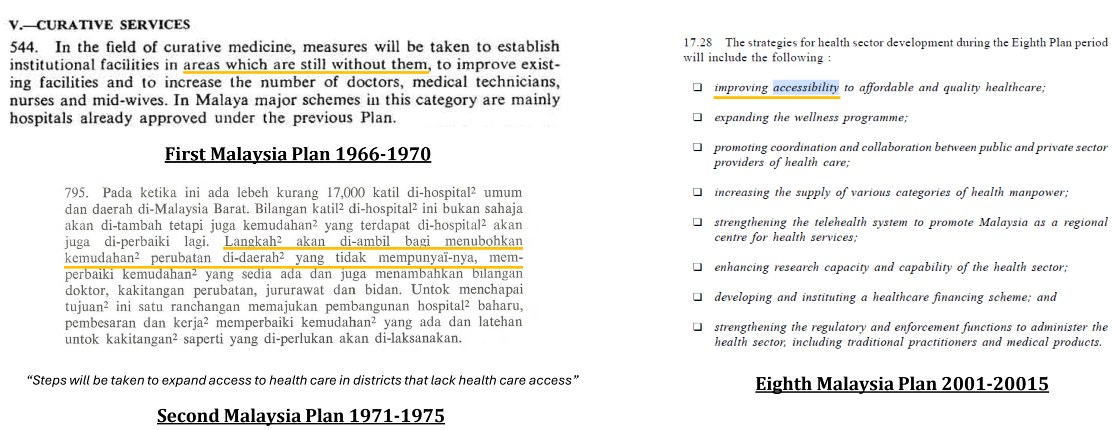
Note: This figure shows the distribution of doctors across different districts in Malaysia in the year 2000. Data is from the Malaysian Census 2000.

Figure A.7: Distribution of Birth Delivery Prices in Private Hospitals (MYR)



Note: This figure shows the distribution of normal (vaginal) delivery and caesarean section prices in private hospitals in Malaysia. Most maternity packages offer only normal delivery packages, but some private hospitals do offer caesarean section packages as well.

Figure A.8: Selected Excerpts from Malaysia Planning Documents



V.—CURATIVE SERVICES

544. In the field of curative medicine, measures will be taken to establish institutional facilities in areas which are still without them, to improve existing facilities and to increase the number of doctors, medical technicians, nurses and mid-wives. In Malaya major schemes in this category are mainly hospitals already approved under the previous Plan.

First Malaysia Plan 1966-1970

795. Pada ketika ini ada lebeh kurang 17,000 katil di-hospital² umum dan daerah di-Malaysia Barat. Bilangan katil² di-hospital² ini bukan sahaja akan di-tambah tetapi juga kemudahan² yang terdapat di-hospital² akan juga di-perbaiki lagi. Langkah² akan di-ambil bagi menubohkan kemudahan² perubatan di-daerah² yang tidak mempunyaï-nya, memperbaiki kemudahan² yang sedia ada dan juga menambahkan bilangan doktor, kakitangan perubatan, jururawat dan bidan. Untok menchapai tujuan² ini satu ranchangan memajukan pembangunan hospital² baharu, pembesaran dan kerja² memperbaiki kemudahan² yang ada dan latehan untok kakitangan² saperti yang di-perlukan akan di-laksanakan.

"Steps will be taken to expand access to health care in districts that lack health care access"

Second Malaysia Plan 1971-1975

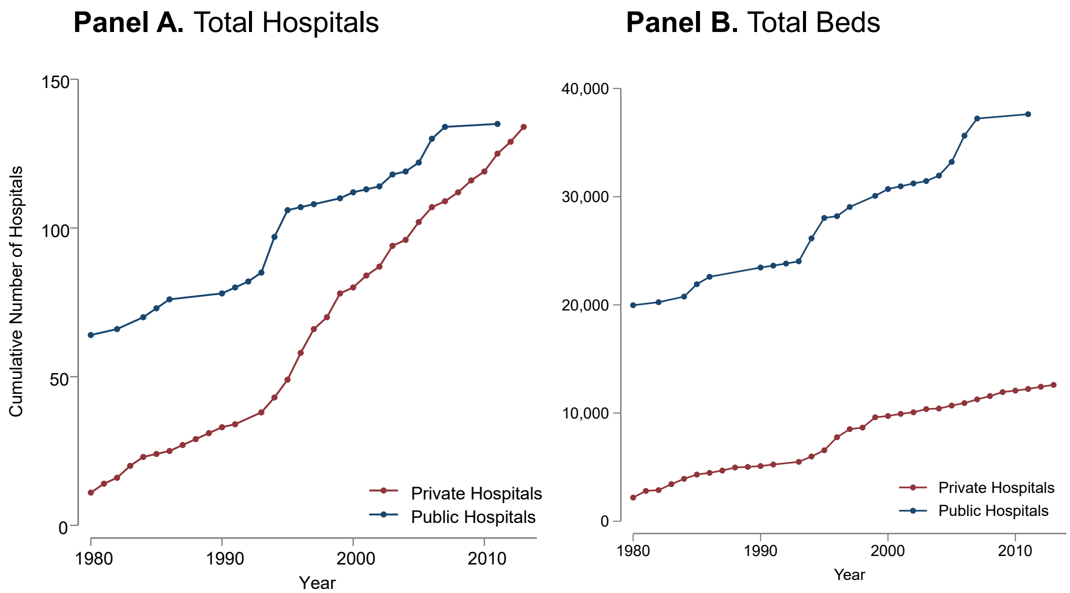
17.28 The strategies for health sector development during the Eighth Plan period will include the following :

- *improving accessibility to affordable and quality healthcare;*
- *expanding the wellness programme;*
- *promoting coordination and collaboration between public and private sector providers of health care;*
- *increasing the supply of various categories of health manpower;*
- *strengthening the telehealth system to promote Malaysia as a regional centre for health services;*
- *enhancing research capacity and capability of the health sector;*
- *developing and instituting a healthcare financing scheme; and*
- *strengthening the regulatory and enforcement functions to administer the health sector, including traditional practitioners and medical products.*

Eighth Malaysia Plan 2001-20015

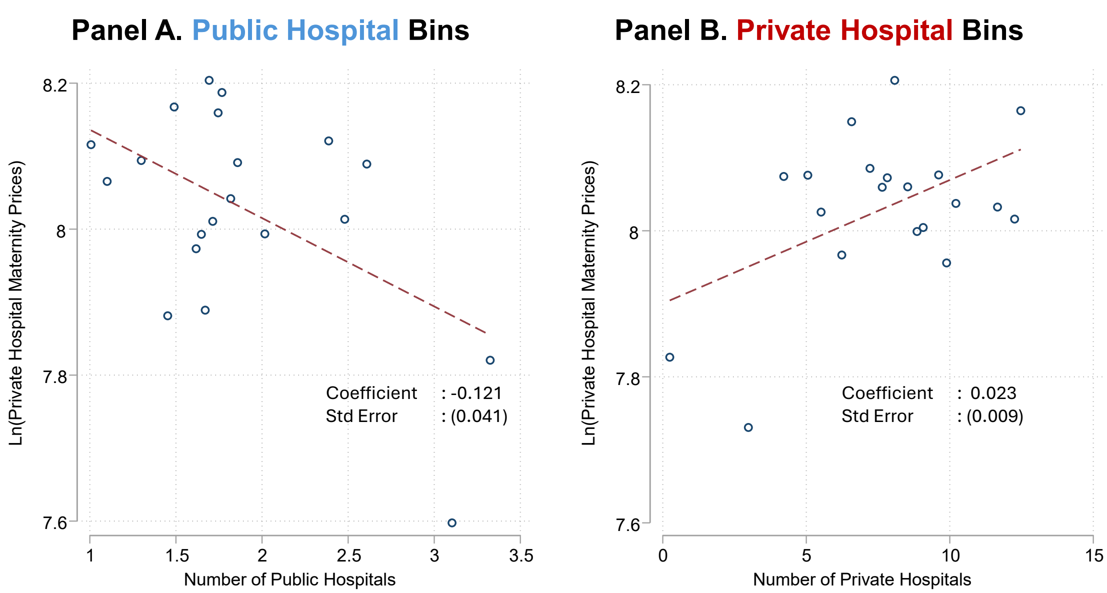
Note: These excerpts are taken from various planning documents related to healthcare development in Malaysia. These panels show the commitment of the Malaysian government in prioritizing access to healthcare.

Figure A.9: Total Count and Beds by Public and Private Hospitals



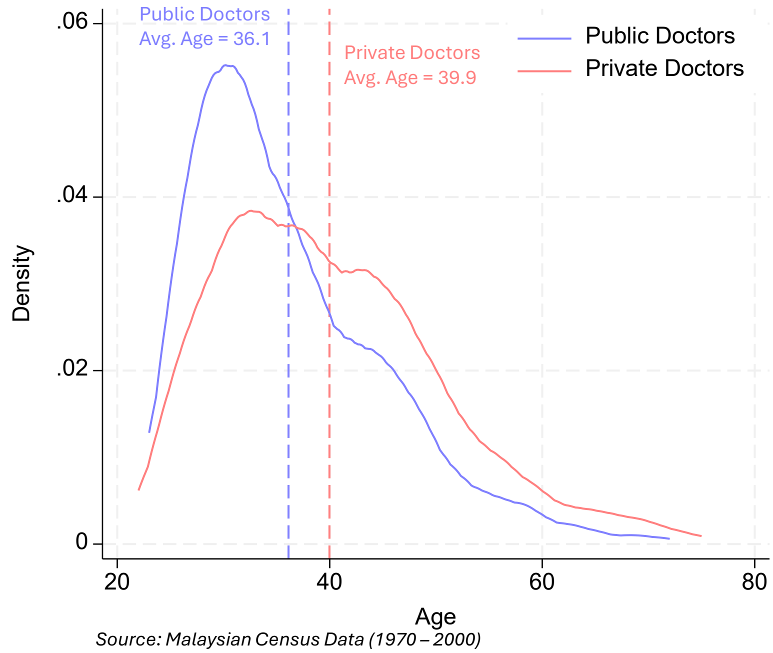
Note: This figure shows the total count of hospitals and the number of beds available in public and private hospitals in Malaysia between 1980 and 2014.

Figure A.10: Private Hospital Normal Delivery Prices by Number of Public/Private Hospitals in District



Note: Panel A figure shows a binscatter of private hospital normal delivery prices against the number of public hospitals within the same district. Panel B shows a binscatter against the number of private hospitals within the same district. This figure shows descriptive evidence on public competitive pressures on private pricing.

Figure A.11: Physician Average Age by Public & Private Hospitals



Note: This figure shows the average age of physicians working in public and private hospitals in Malaysia. The difference is approximately 3.8 years–which roughly coincides with the two-year compulsory public housemanship period in the public sector.

Figure A.12: Survey Waiting Time Ratings by Public & Private Hospitals

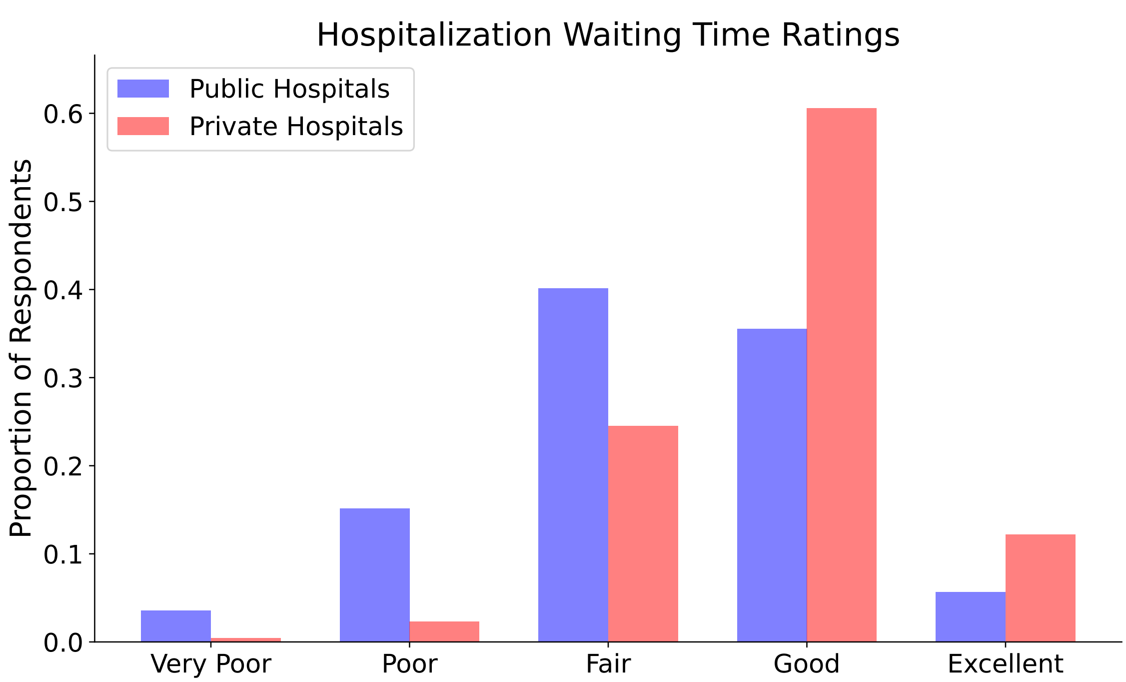
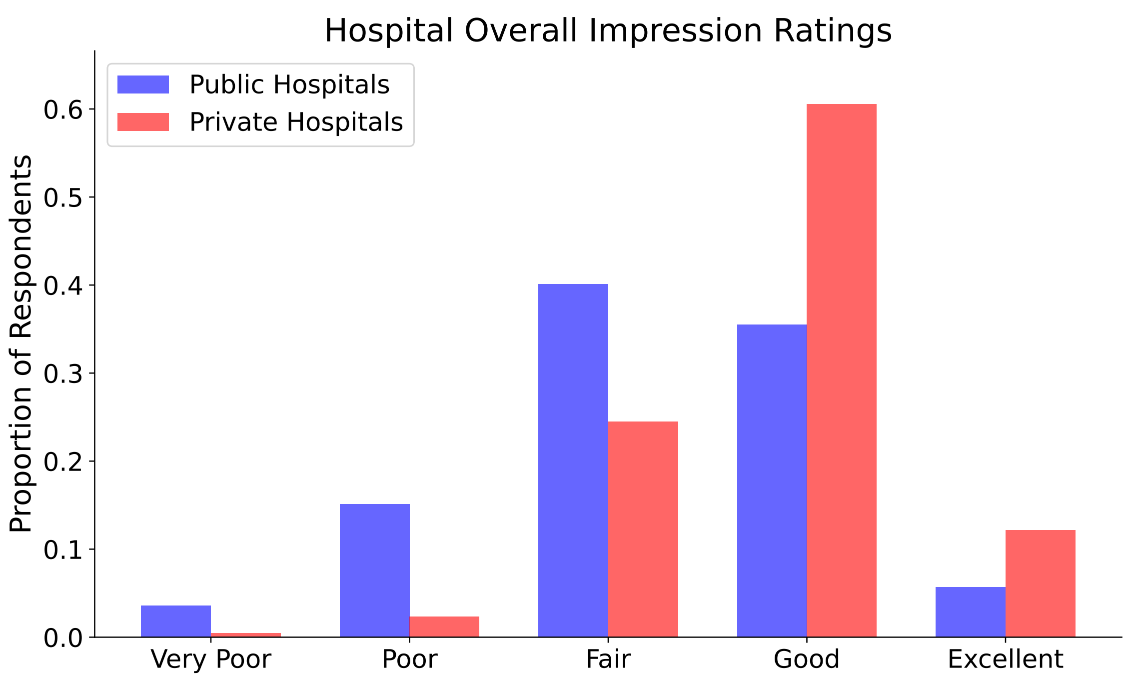


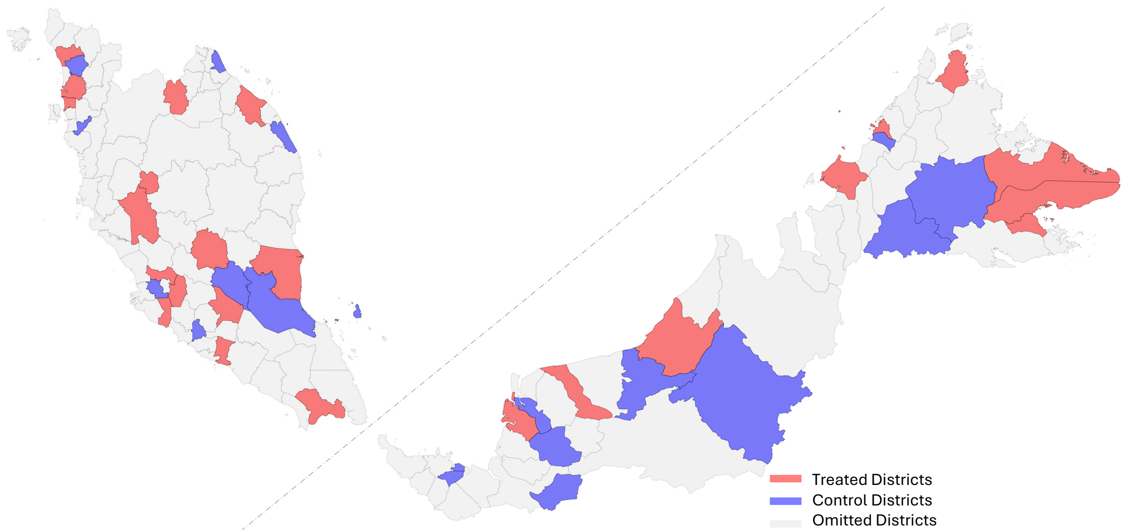
Figure A.13: Hospital Overall Ratings by Public & Private Hospitals



B Further Details on Reduced Form

B.1 Additional Tables and Figures

Figure B.1: Sample of Districts in Event Studies



Note: Red districts are included in the event study design as treated districts, while blue districts are controls. Grey districts are omitted from the event study.

Table B.1: Robustness: Effects of Public Hospitals on Private Specialists by Lag Length

	Private Specialist Physicians (100s)					
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Panel A: Specialist Public Hospitals						
Number of Hospitals	0.547*	0.772	0.743*	1.081**	1.081**	1.081**
	(0.302)	(0.477)	(0.391)	(0.471)	(0.471)	(0.471)
Observations	58	58	60	62	62	62
Mean Dep. Var.	0.309	0.378	0.375	0.411	0.411	0.411
R^2	0.872	0.891	0.891	0.858	0.858	0.858
Panel B: Non-Specialist Public Hospitals						
Number of Hospitals	0.063	0.063	-0.084	-0.084	-0.088	-0.093
	(0.158)	(0.158)	(0.063)	(0.063)	(0.066)	(0.074)
Observations	68	68	66	66	68	68
Mean Dep. Var.	0.159	0.159	0.141	0.141	0.137	0.137
R^2	0.820	0.820	0.880	0.880	0.881	0.881

Notes: Each column presents stacked difference-in-differences estimates with different lag structures. The lag represents the number of years between hospital construction and when effects are assumed to occur. Coefficients represent the effect of each additional public hospital on the number of private specialist physicians (in units of 100s). Panel A shows effects of specialist public hospitals; Panel B shows effects of non-specialist public hospitals. The stacked design compares districts treated in 1970-1980 vs. never-treated (Stack 1) and districts treated in 1980-1991 vs. never-treated (Stack 2), using 1970, 1980, and 1991 census data. All specifications include district-by-stack and year-by-stack fixed effects. Standard errors clustered at the district level are in parentheses. Mean dependent variable is calculated across all observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure B.2: Proportion of Outpatient, Emergency and Inpatient Visits at Private and Public Hospitals

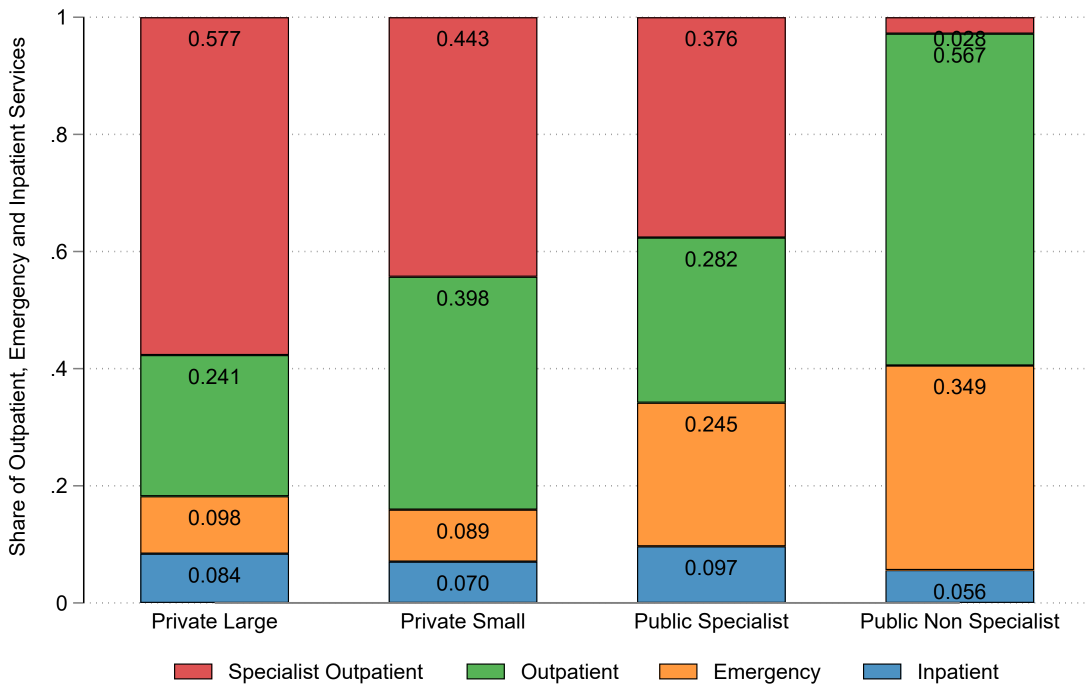
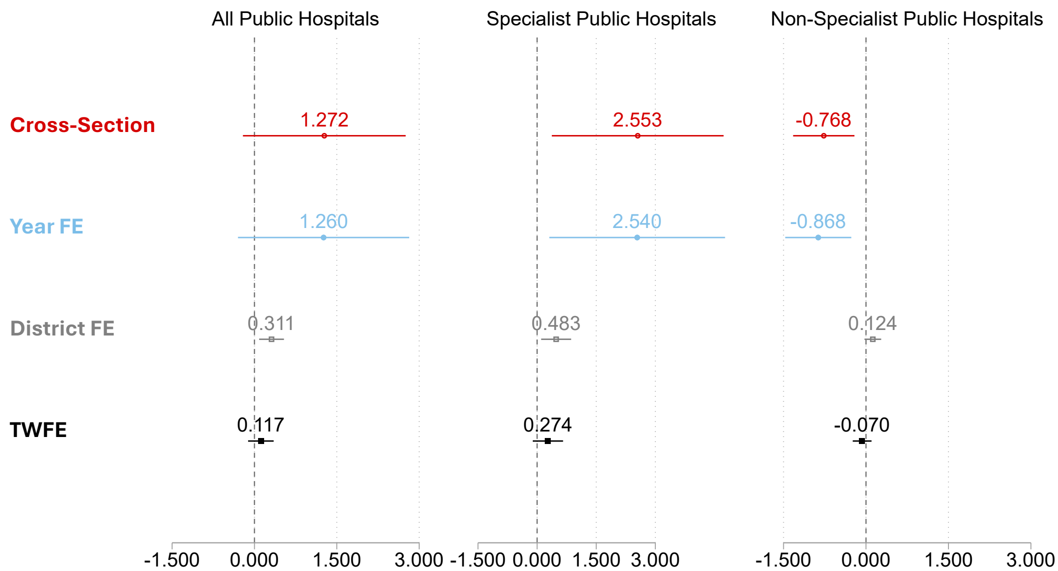


Figure B.3: Balancing Regressions



Notes: This figure shows the results of the balancing regressions. I first predict the number of private hospital using district-level characteristics in Table 1. I then estimate the specification denoted on the y-axis using this predicted outcome as the dependent variable. 'Cross-Section' refers to the estimation Equation 6 but without any fixed effects, and leads and lags replaced by one post $\times$ treat variable. 'Year FE' and 'District FE' add year and district fixed effects, respectively. 'TWFE' includes both sets of fixed effects. The x-axis shows the coefficient on the treatment indicator, with 95% confidence intervals.

B.2 Balancing Regressions

B.3 Synthetic Difference-in-Differences

To address concerns about pre-treatment imbalances between treatment and control districts, I re-estimate the main results using the synthetic difference-in-differences (SDID) estimator (Arkhangelsky et al., 2021). This method addresses potential confounding by constructing synthetic control units that optimally weight both untreated districts and pre-treatment time periods to better match the treated units' characteristics and trends.

Table B.2 presents the average treatment effects using the SDID estimator. The results closely mirror the main findings from the event study analysis. All types of public hospitals increase private hospital entry by 0.406 hospitals on average (which is similar compared to 0.465 in the main specification). When disaggregating by hospital type, specialist public hospitals generate a positive and significant effect of 0.692 additional private hospitals (again, similar compared to 0.785 in the main results), while non-specialist public hospitals show a small and statistically insignificant negative effect of -0.016 hospitals.

Figure B.4 shows the dynamic treatment effects over time using the SDID framework. Panel A shows that the positive effect of all public hospitals increases gradually, becoming statistically significant around year 3 and growing to approximately 0.5 additional private hospitals by year 7. Panel B shows that specialist public hospitals drive this pattern, with effects beginning in year 2 and reaching nearly 1 additional private hospital by the end of the observation period. Panel C in contrast, shows that non-specialist public hospitals have negligible effects throughout the post-treatment period, with confidence intervals consistently encompassing zero.

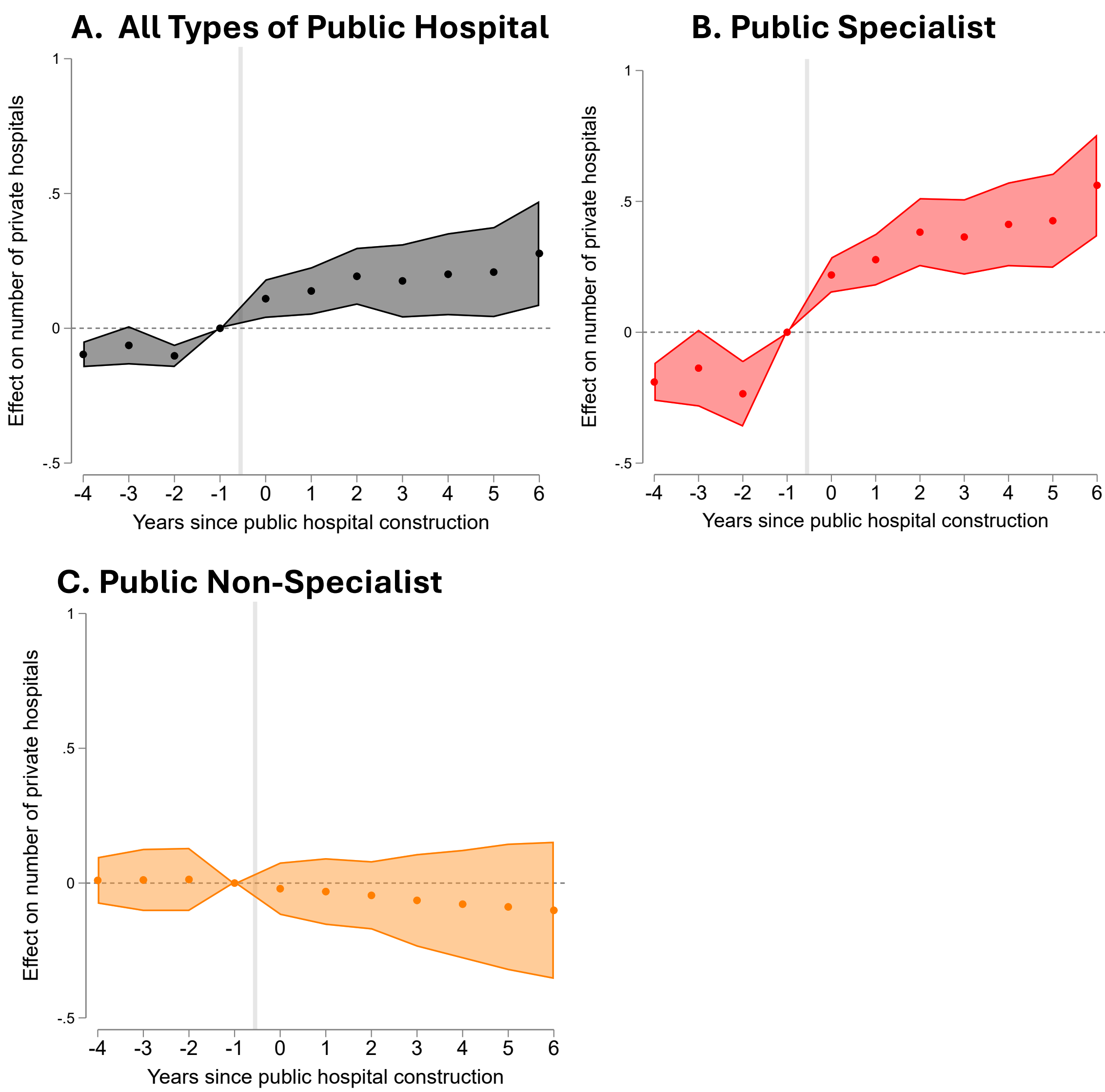
Overall, the similarities in findings between the main event study results and these SDID estimates provides strong evidence that the findings are robust to concerns about pre-treatment differences between treatment and control districts

Table B.2: Average Treatment Effects on Private Entrants - Synthetic Difference-in-Differences

	Count of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	0.406**		
	(0.168)		
E2: Specialist public hospitals		0.692**	
		(0.275)	
E3: Non-specialist public hospitals			-0.016
			(0.030)
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Estimator	SDID	SDID	SDID

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Each column presents results using the Synthetic DiD estimator (Arkhangelsky et al., 2021). SEs in parentheses.

Figure B.4: Synthetic Difference-in-Differences: Dynamic Treatment Effects



Note: Panel A plots the dynamic treatment effects from Arkhangelsky et al. (2021) with all types of public hospitals as treatment units. Panel B are for specialist public hospitals while Panel C is for non-specialist public hospitals. The control units are selected using the Synthetic DiD procedure. The shaded area represents the 95% confidence interval.

B.4 Matching

To further address concerns about pre-treatment imbalances, I use coarsened exact matching (CEM) to balance treatment and control districts on key observable characteristics that showed the largest imbalances in the raw data: rurality and the number of existing public hospitals in 1996. The matching procedure reduces the sample from a total of 47 districts (25 treatment, 22 control) to 28 districts (12 treated, 16 control).

Table B.3 shows that matching removes all statistically significant differences between treatment and control groups. Most notably, the previously significant differences in population size (p=0.037) and rurality (p=0.063) are no longer present.

Figure B.5 presents the event study results using the matched sample. The average post-treatment effect is 0.108 additional private hospitals, representing a 31.4 percent increase relative to the pre-treatment mean of 0.344 hospitals in the matched sample. This is similar to the main specification, which showed a 47.5 percent increase (0.465 relative to a mean of 0.979).

I focus this robustness check on all types of public hospitals rather than disaggregating by hospital type because the sample reduction is substantial. Splitting the already-small matched sample by treatment type would yield insufficient variation for reliable inference, particularly given that specialist public hospitals represent only a subset of the 12 remaining treated districts.

Figure B.5: Event Study of Matching on Private Hospital Entrants

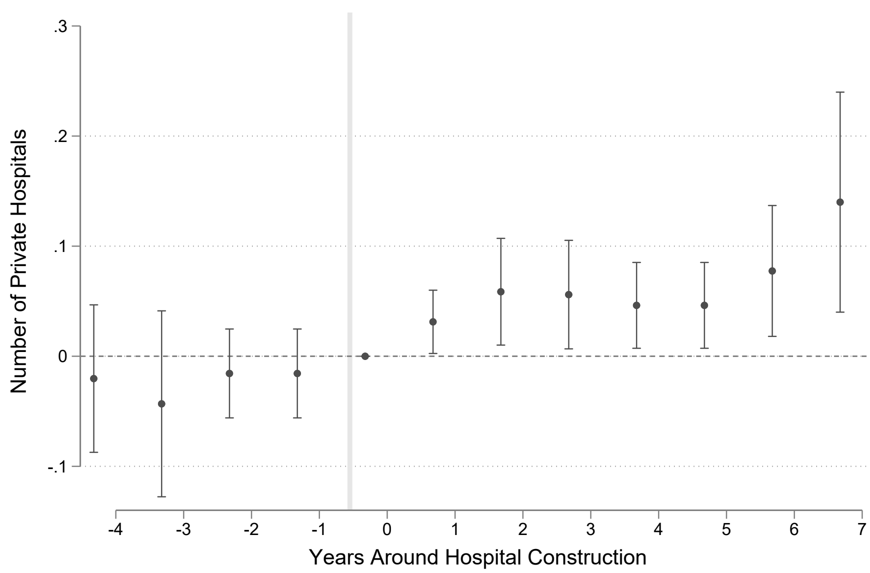


Table B.3: Post-Matching Summary Statistics by Treatment Status

Variable	Treated (N=12)	Never Treated (N=16)	Difference	P-value
Panel A. Demographics				
Log Population	11.186 (0.870)	11.001 (0.869)	0.185	0.582
Rural Population Share	0.843 (0.224)	0.850 (0.262)	-0.007	0.936
Chinese Share	0.127 (0.116)	0.170 (0.198)	-0.043	0.505
Malay Share	0.402 (0.362)	0.431 (0.384)	-0.029	0.839
Indian Share	0.061 (0.077)	0.039 (0.063)	0.022	0.429
Married Share	0.375 (0.015)	0.398 (0.041)	-0.023	0.078*
Financial Services Employment Share	0.005 (0.015)	0.006 (0.011)	-0.001	0.894
Panel B. Education				
College/University Education	0.012 (0.014)	0.014 (0.017)	-0.002	0.772
Secondary Education Completed	0.170 (0.077)	0.205 (0.064)	-0.035	0.200
Primary Education Completed	0.188 (0.048)	0.191 (0.038)	-0.003	0.859
Some Primary Education	0.216 (0.028)	0.209 (0.031)	0.007	0.550
Panel C. Age Distribution				
Age <1	0.031 (0.008)	0.026 (0.008)	0.005	0.106
Age 1–4	0.119 (0.019)	0.110 (0.020)	0.009	0.233
Age 5–18	0.340 (0.039)	0.314 (0.044)	0.026	0.119
Age 19–45	0.369 (0.063)	0.388 (0.062)	-0.019	0.451
Age 46–60	0.095 (0.031)	0.101 (0.031)	-0.006	0.612
Age 61–74	0.034 (0.017)	0.047 (0.020)	-0.013	0.077*
Age >74	0.012 (0.009)	0.015 (0.008)	-0.003	0.347
Panel D. Health Facilities				
Number of Private Hospitals	0.094 (0.401)	0.375 (1.500)	-0.281	0.534
Number of Public Hospitals	0.125 (0.345)	0.125 (0.342)	0.000	1.000
Number of Private Doctors	12.500 (36.927)	18.750 (62.915)	-6.250	0.762
Distance to Nearest Public Hospital (km)	33.054 (13.585)	36.570 (40.181)	-3.516	0.774
Distance to Nearest Private Hospital (km)	118.454 (88.809)	113.839 (122.953)	4.615	0.913

Notes: Standard deviations in parentheses. Difference = Treated - Never Treated. P-values from two-sample t-tests. Sample reduced from 47 districts to 28 districts (12 treated, 16 control) after coarsened exact matching.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.5 Additional Robustness Checks

Table B.4: Main Effects Robustness: Dropping Multiple Treated Districts

	Count of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	0.457***		
	(0.151)		
E2: Specialist public hospitals		0.937***	
		(0.114)	
E3: Non-specialist public hospitals			-0.171***
			(0.009)
Mean Outcome	1.282	1.709	0.631
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N Districts $\times$ Year	792	594	594
R^2	0.953	0.957	0.930
Unique Events	22	11	11
Estimator	SA	SA	SA

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Each column presents results from separate regressions using the Sun and Abraham (2021) estimator. Standard errors in parentheses clustered at the district level.

Table B.5: Main Effects Robustness: Last-Treated as Control

	Count of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	0.684***		
	(0.081)		
E2: Specialist public hospitals		0.599***	
		(0.088)	
E3: Non-specialist public hospitals			—
Mean Outcome	0.979	1.278	—
District Fixed Effects	Yes	Yes	—
Year Fixed Effects	Yes	Yes	—
N Districts × Year	.	.	—
R^2	0.980	0.975	—
Unique Events	25	14	—
Estimator	SA	SA	—

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Columns (1) and (2) show results using last-treated districts as controls. Column (3) is not estimated because both last-treated control districts and non-specialist treated districts had zero private hospital entrants, providing no variation for identification. SEs in parentheses clustered at district level.

Table B.6: Post-Treatment Effects on Private Hospital Entry: Comparison of Estimators

	SA	BJSp	CS	DdH
	(1)	(2)	(3)	(4)
All public hospitals	0.465***	0.296	1.153***	0.289
	(0.094)	(0.267)	(0.323)	(0.177)
Specialist public hospitals	0.785***	0.659**	1.424***	0.558***
	(0.108)	(0.292)	(0.336)	(0.191)
Non-specialist public hospitals	-0.171***	-0.281	-0.208	-0.119
	(0.009)	(0.236)	(0.181)	(0.110)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Each column presents post-treatment average effects using different estimators for staggered DiD designs.

B.5.1 Additional Heterogeneity: Districts with and without Existing Public Hospitals

To examine whether the main results are driven by particular types of districts, I disaggregate the analysis by whether districts had existing public hospitals prior to the treatment period. Among the 25 new public hospitals constructed, eight were built in areas with pre-existing public hospitals while 17 were built in previously underserved areas. Table B.7 presents these results.

Specialist public hospitals generate crowd-in effects in both types of districts, but the magnitude is substantially larger in districts with existing public hospital infrastructure. In districts with no existing public hospitals, specialist hospitals increase private hospitals by 17.4 percent (0.093 relative to a mean of 0.533). In areas with at least one existing public hospital, the effect is much larger at 95.2 percent (1.360 relative to a mean of 1.429). This multiplier effect suggests that medical infrastructure creates complementarities that strengthen the physician training channel. Districts with established public hospitals likely have more developed medical infrastructure that enhance the spillover benefits when new specialist facilities are added. Among districts with existing public hospitals that receive new specialist facilities, approximately half have existing non-specialist hospitals while the other half have existing specialist hospitals. However, further disaggregating the analysis to examine these subgroups would stretch the limited data too thin to draw reliable conclusions about the specific mechanisms driving the multiplier effect.

Non-specialist hospitals continue to crowd out private entry in both types of districts, reducing private hospitals by 50.8 percent (0.164 relative to a mean of 0.323) in districts without existing public hospitals and by 47.0 percent (0.196 relative to a mean of 0.417) in districts with existing public infrastructure. This pattern suggests that non-specialist hospitals generate consistent competitive effects regardless of existing medical infrastructure. Overall, the results suggest that the crowd-in effects of specialist hospitals are not driven by a particular subset of districts, but rather represent a general phenomenon that multiplies in areas with stronger medical infrastructure, though the precise mechanisms behind this multiplier effect remain unclear given the data limitations.

Table B.7: Effects on Private Entry By Districts with and without Existing Public Hospitals

	Number of Private Hospitals			
	Districts with no Public Hospital		Districts with ≥1 Public Hospital	
	(1)	(2)	(3)	(4)
E2: Specialist public hospitals	0.093		1.360	
	(0.030)		(0.152)	
E3: Non-specialist public hospitals		-0.164		-0.196
		(0.009)		(0.042)
Pre-Treatment Mean	0.533	0.323	1.429	0.417
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	540	558	504	432
R^2	0.923	0.929	0.967	0.933
Unique events	8	9	6	2
Estimator	SA	SA	SA	SA

Notes: Each column presents results from separate regressions using the Sun and Abraham (2021) estimator. Standard errors in parentheses are clustered at the district level. The dependent variable is the number of private hospitals in a district. Columns 1-2 show results for districts with no existing public hospitals; columns 3-4 show results for districts with at least one existing public hospital prior to the treatment period.

C Further Details on Model and Estimation

C.1 Data Construction

This section provides details on how I constructed my final dataset for demand estimation. In 2013, there were a total of 269 hospitals alongside 70 maternity centers. Single specialty hospitals such as cardiology specialist centers are omitted. The final dataset consists of inpatient providers with at least one birth delivery recorded at the facility.

Individuals face a choice between public and private hospitals, an outside option of traditional/home births, or a maternity center. For each market with at least one maternity center, I sum the total number of birth deliveries from all maternity centers in that district and treat it as one additional choice representing maternity centers. This amounts to 19 districts with at least one maternity center. For prices, eight districts had maternity centers, of which I do not have prices for. Maternity center prices range between MYR 1,800 and MYR 3,588, with a median price of MYR 2,500. For these districts with missing prices, I impute the median price of MYR 2,500.

C.2 Demand Details

I specify a discrete choice model of hospital selection for birth deliveries in Malaysia using Berry et al. (1995, 2004) and estimate the model using the PyBLP Python package (Conlon and Gortmaker, 2020, 2023). The model incorporates both aggregate market share data and micro moments from a national survey of potential mothers to identify demand parameters and calculate expected profits from entering specific districts.

I model $d = 1, 2, \ldots, \mathcal{D} = 95$ district-level markets where child-seeking women choose among available public and private hospitals, alongside private maternity centers for birth deliveries. In each market t, I define the choice set to include $j = 1, 2, \ldots, J_t^{pub}$ public hospitals priced at MYR 100 per delivery, $j = J_t^{pub} + 1, \ldots, J_t$ private hospitals with profit-maximizing prices that vary by patient income group, and $j = 0$ representing the outside option of traditional or home births. Each private hospital j is operated by firm f, where firms are either the government or private entrepreneurship groups. I treat public hospitals as having an exogenously fixed price at MYR 100. I specify the indirect utility of child-seeking woman i in district d from choosing j following the standard BLP specification:

$$U_{ijd} = \delta_{jd} + \mu_{ijd} + \epsilon_{ijd}$$

I define the mean utility as $\delta_{jd} = \alpha p_{jd} + X_{1jd}\beta + \xi_{jd}$, where p_{jd} represents the price per delivery in thousands of MYR (varying by income groups: low, middle and high income groups), X_{1jd} contains standardized hospital characteristics including congestion (bed occupancy rate), staff, number of specialties, and hospital type indicators, $\alpha < 0$ captures price sensitivity, β represents parameters on hospital characteristics, and ξ_{jd} denotes unobserved hospital quality.

I model individual heterogeneity through the random coefficients specification $\mu_{ijd} = X_{2jd}(\Sigma\nu_{id}' + \Pi a_{id}')$, where X_{2jd} represents a subset of X_{1jd} including a constant, price, and private hospital indicator. The agent demographic variables a_{id} capture district-level characteristics including low income, mid income, high income shares, distance to nearest hospital, private insurance coverage, and chronic disease prevalence. I assume unobserved individual heterogeneity ν_{id} follows a Type I Extreme Value distribution, Σ represents a 3×3 Cholesky matrix governing unobserved taste heterogeneity, and Π forms a 3×7 matrix measuring how preferences vary with observable demographics.

Related to the utility specification in Equation 8, the components of the main text utility map to the BLP structure are as follows: the mean utility δ_{jd} incorporates the hospital characteristics $H_j\beta$ from Equation 8 along with any baseline price effects that do not vary by individual income group. The individual heterogeneity term μ_{ijd} captures the income group-specific price sensitivity $\alpha_i p_j$, the travel disutility $\gamma_i \text{distance}_{ij}$, and the private hospital interactions with individual attributes $\text{private}_j(Z_i)$ from the main specification. The random error term ε_{ij} corresponds directly to ε_{ijd} in this appendix. This decomposition allows me to separate hospital-level mean preference from individual-specific taste variations. Specifically, I implement the income-price interactions through the random coefficients specification $\mu_{ijd} = X_{2jd}(\Sigma\nu'_{id} + \Pi d'_{id})$, where the Π matrix captures how price sensitivity and private hospital preferences vary with district-level demographics including the income group shares that determine the α_i and $\text{private}_j(Z_i)$ terms from Equation 8.

I model choice probabilities following the mixed logit form $s_{ijd} = \frac{\exp(V_{ijd})}{1+\sum_{k \in J_d} \exp(V_{ikd})}$, with aggregate market shares computed by integrating over the distribution of heterogeneity: $s_{jd} = \int s_{ijd} dF(\nu_{id}, d_{id})$.

On the supply side, I focus exclusively on private hospitals, treating public hospital pricing as exogenously determined. Private hospitals set different prices for patients from different income groups. I model private hospital f in market t as choosing prices for its hospitals $J_{fd} \subseteq J_t$ across income groups to maximize profits

$$\pi_{fd} = \sum_{j \in J_{fd}} \sum_{g \in \{low, mid, high\}} (p_{jdg} - c_{jd}) \cdot s_{jdg} \cdot M_{tg}$$

where M_{tg} represents the total number of births in district t from income group g. The multi-product Bertrand pricing first-order conditions yield the standard markup equation $p_{jdg} - c_{jd} = \eta_{jdg} = [\Delta^{-1} s]_{jdg}$, where Δ represents demand derivatives across products and income groups and $\mathscr{H}$ denotes the ownership matrix with $\mathscr{H}_{jk} = 1$ if hospitals j and k are owned by the same firm and zero otherwise.

Rather than imposing a parametric cost function, I recover marginal costs directly from the first-order conditions using $c_{jd} = p_{jdg} - \eta_{jdg}$. The recovered marginal costs represent the marginal cost of providing an additional birth delivery at each private hospital (which is distinct from the fixed cost or operational costs of entry).

To identify the demand parameters, particularly the distribution of random coefficients, I incorporate micro moments from a national survey of potential mothers. I specify these moments as $\bar{g}_{M,m} = f_m(\bar{v}) - f_m(v)$, matching observed versus simulated conditional demographic expectations. Specifically, I include moments for the expected probability that private hospital users belong to different income categories, their average distance to hospitals, insurance coverage rates, and chronic disease prevalence.

I estimate the model by GMM, minimizing the objective function $\min_\theta q(\theta) = \bar{g}(\theta)' W \bar{g}(\theta)$, where θ includes the non-concentrated parameters Σ and Π, and $\bar{g}(\theta)$ contains both demand-side moments $\bar{g}_D = \frac{1}{N}\sum_{j,d} Z'_{D,jd}\xi_{jd}$ and the micro moments $\bar{g}_M$ described above. My identification relies on differentiation instruments following Gandhi and Houde (2025), which measure local competition based on other hospitals' characteristics within each district, combined with the micro moments that help pin down the distribution of random coefficients through demographic sorting patterns. The fixed pricing of public hospitals at MYR 100 provides additional variation for identifying the price coefficient.

I tabulate the demand estimates in Table C.1 and the fitted micro moments in Table C.2. The results show strong income-based price discrimination in the market. Only 7.9 percent of low-income individuals use private hospitals, compared to 23.8 percent for mid-income and 68.5 percent for high-income consumers. As expected, low-income consumers show the strongest price sensitivity (-1.92), followed by mid-income consumers (-1.46), while high-income consumers are the least price sensitive (-0.723) though still negatively affected by price increases. The absence of a statistically significant base price sensitivity indicates that income heterogeneity is crucial for identifying price effects in this market.

The micro moments demonstrate the importance of considering the income distribution among private hospital users. The observed micro moments show that private hospital users are predominantly high-income (68.5%), followed by mid-income (23.8%) and low-income (7.9%) consumers. This distribution aligns with the estimated price sensitivities and suggests that private hospitals successfully target higher-income segments through their pricing strategies.

Hospital characteristics reveal clear consumer preferences. The congestion coefficient (0.464) with its negative squared term (-0.214) suggests consumers prefer moderately busy hospitals, likely viewing some congestion as a signal of quality while avoiding overly crowded facilities. Consumers show strong preferences for hospitals with more specialties (0.659), while the staff coefficient (-0.026) suggests that raw staff count is not a key quality indicator for consumers.

The large positive coefficient on private hospital usage among insured individuals (2.96) indicates that insurance coverage, despite not covering maternity care directly, strongly predicts private hospital choice. This likely reflects choice inertia among families who are regular private healthcare users. The negative coefficient on chronic conditions (-1.21) suggests that women with chronic conditions may prefer public hospitals, possibly due to better coordination with existing public sector care or cost considerations.

Distance effects are captured through the private hospital interaction (-1.37), showing that consumers are significantly less willing to travel long distances for private hospitals, consistent with the local nature of birth delivery decisions.

The hospital type fixed effects reveal a clear hierarchy in consumer preferences. The large private hospital fixed effect (3.59) indicates a substantial preference for private facilities beyond the specific characteristics controlled for, while the maternity center coefficient (2.44) suggests these specialized private facilities are particularly attractive. Non-specialist hospitals (1.49) and minor specialist hospitals (0.795) also show positive preferences relative to the omitted category of major specialist hospitals.

These estimates suggest that private hospital entry would be most profitable in high-income districts, where consumers demonstrate both ability to pay higher prices and willingness to choose between private options based on price and quality characteristics. The income-based pricing model reveals sophisticated market segmentation that allows private hospitals to extract consumer surplus while maintaining access across different income groups.

Table C.1: Demand Estimates Across Specifications

	Specification			
	OLS Logit	IV Logit	Random Coeffs (no micro)	Rand. Coeffs Microdata
	(1)	(2)	(3)	(4)
A. Price coefficients				
Base price sensitivity	-0.668^{***}	-3.030^{***}	-0.076	-1.790^{**}
	(0.133)	(1.010)	(2.960)	(0.859)
Low income × Price	–	–	1.070	-1.710^{***}
			(1.050)	(0.365)
Mid income × Price	–	–	-0.616	-1.070^{***}
			(14.600)	(0.299)
High income × Price	–	–	-2.470	-0.014
			(30.600)	(0.404)
B. Distance effects				
Distance (km)	–	–	-0.988	-0.492
			(3.320)	(2.540)
C. Hospital characteristics				
Congestion (SD)	0.252	0.554^{**}	0.131	0.363
	(0.163)	(0.231)	(0.492)	(0.297)
Congestion Sq. (SD)	-0.122	-0.138	-0.302	-0.150
	(0.104)	(0.138)	(0.317)	(0.134)
Staff (SD)	-0.280^{*}	-0.090	-0.289	-0.189
	(0.153)	(0.140)	(0.544)	(0.235)
No. Specialties (SD)	0.439^{**}	0.377	0.386	0.494
	(0.214)	(0.262)	(0.660)	(0.302)
D. Taste heterogeneity				
Private × Insurance	–	–	-0.618	3.100^{***}
			(39.100)	(0.658)
Private × Chronic	–	–	0.771	-1.380^{**}
			(12.700)	(0.588)
E. Hospital–type fixed effects (Base: Public Specialist)				
Public Non-Specialist	0.720	1.300^{**}	0.728	1.340^{*}
	(0.482)	(0.581)	(1.200)	(0.755)
Private Maternity Centers	0.947^{*}	7.590^{***}	-1.740	5.640^{*}
	(0.480)	(2.760)	(6.000)	(3.010)
Private Large Hospitals	0.228	8.430^{**}	-2.180	5.610
	(0.340)	(3.350)	(16.000)	(3.610)
Private Small Hospitals	-1.280^{***}	6.360^{**}	-4.530	3.200
	(0.259)	(3.120)	(15.200)	(3.530)

Notes: Robust s.e.'s in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$. SD = variable is z-scored. The baseline for hospital-type fixed effects is Public Specialist. Column (2) uses Gandhi and Houde (2019) instruments. Columns (3)–(4) allow random coefficients on *price* and the *private-hospital* dummy; in (4) price sensitivity is fully loaded on demographics (income-group specific). Column (4) additionally matches income, insurance and chronic-condition micro moments from NHMS survey data. Private hospitals set income-group-specific prices in the preferred specification (4).

Table C.2: Estimated Micro Moments (Column 4)

Moment	**Observed**	**Estimated**	**Difference**	**Observations**
A. Income–Private Hospital Interactions				
$E[\text{low}_i \mid \text{private}_j]$	0.076	0.079	-0.003	5,440
$E[\text{high}_i \mid \text{private}_j]$	0.688	0.681	$+0.007$	5,440
B. Insurance and Chronic Condition Interactions				
$E[\text{insurance}_i \mid \text{private}_j]$	0.602	0.598	$+0.004$	5,440
$E[\text{chronic}_i \mid \text{private}_j]$	0.633	0.635	-0.002	5,440

Notes: Micro moments are conditional expectations computed from NHMS survey data across all markets. Differences are Observed minus Estimated. Values are rounded to three decimal places. Income shares refer to proportions of private-hospital users from each income group.

C.3 Estimating Expected Profits from Entry

For counterfactual analysis of private hospital entry, I simulate adding an "average" private hospital to districts currently without private facilities. I assign the entering hospital characteristics equal to the mean of existing private hospitals: $\bar{X}_{1,new} = \frac{1}{N_{private}} \sum_{j \in J_{private}} X_{1jt}$. Following entry, the choice set in district t expands to include the original public hospitals with unchanged prices, the new private hospital with optimally set price, and the outside option. I calculate expected profits for the entering hospital as $\hat{\pi}_{new,t} = (p_{new,t} - c_{new,t}) \cdot s_{new,t} \cdot M_t$, where market shares are predicted from our estimated demand model, marginal costs are recovered using the multi-product Bertrand markup, and the entry price assumes profit-maximizing behavior given existing public hospital prices.

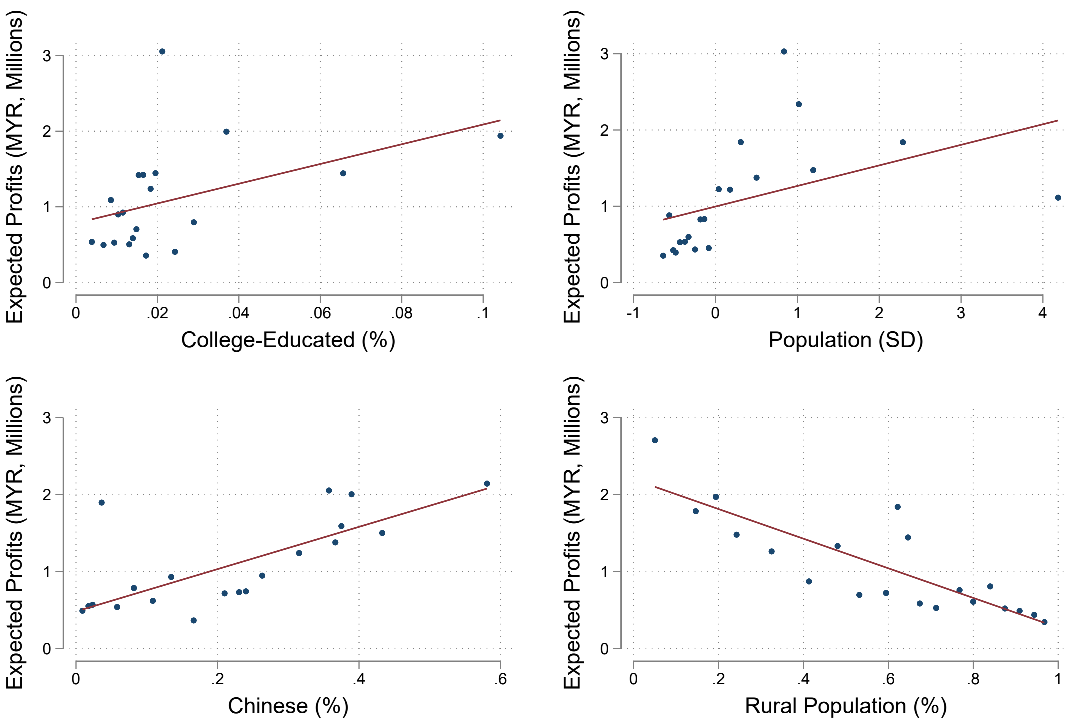
For districts that currently contain private hospitals, I aggregate total private sector profits at the market level by summing individual hospital profits: $\Pi_{private,t} = \sum_{j \in J_{private,t}} \pi_{jt}$. These market-level profit estimates, combined with the simulated entry profits for districts without private hospitals, provide the expected payoff structure for the dynamic entry model beginning in 1996. This approach implicitly captures the fact that potential entrants form expectations about market profitability based on the estimated static Bertrand competition outcomes. The aggregated profits represent the total market potential that new entrants would compete for, while the simulated entry profits indicate the expected returns from entering previously unserved districts.

Table C.3: Demand Estimates Across Specifications (Robustness Check - Remove Hospitals with Missing Price/Admissions)

	Specification			
	OLS Logit	IV Logit	Random Coeffs (no micro)	Rand. Coeffs Microdata
	(1)	(2)	(3)	(4)
A. Price coefficients				
Base price sensitivity	-0.491^{***}	-1.610^{***}	0.000	-0.476
	(0.075)	(0.596)		(0.695)
Low income × Price	–	–	0.363	-1.380^{***}
			(2.260)	(0.501)
Mid income × Price	–	–	-1.600	-0.622^{**}
			(6.560)	(0.303)
High income × Price	–	–	-0.716	0.561
			(7.510)	(0.411)
B. Distance effects				
Distance (km)	–	–	-0.639	-0.740
			(7.840)	(2.510)
C. Hospital characteristics				
Congestion (SD)	0.235^{**}	0.379^{***}	0.127	0.114
	(0.106)	(0.147)	(0.290)	(0.305)
Congestion Sq. (SD)	-0.145^{**}	-0.175^{**}	-0.125	-0.215
	(0.074)	(0.086)	(0.447)	(0.136)
Staff (SD)	-0.065	0.032	-0.037	-0.082
	(0.077)	(0.108)	(0.211)	(0.203)
No. Specialties (SD)	0.208	0.113	0.077	0.304
	(0.158)	(0.192)	(1.050)	(0.338)
D. Taste heterogeneity				
Private × Insurance	–	–	1.280	3.530^{***}
			(33.300)	(1.130)
Private × Chronic	–	–	2.610	-1.530^{**}
			(20.900)	(0.671)
E. Hospital–type fixed effects (Base: Public Specialist)				
Public Non-Specialist	0.100	0.236	0.106	0.356
	(0.313)	(0.358)	(1.130)	(0.767)
Private Maternity Centers	0.857^{***}	3.950^{**}	-0.448	1.340
	(0.301)	(1.630)	(3.570)	(2.560)
Private Large Hospitals	0.154	4.040^{*}	-3.140	0.523
	(0.217)	(2.080)	(14.900)	(2.940)
Private Small Hospitals	-1.070^{***}	2.460	-4.990	-1.550
	(0.177)	(1.830)	(16.000)	(2.810)

Notes: Robust s.e.'s in parentheses. This table uses a restricted sample that excludes hospitals with missing prices or admissions. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$. SD = variable is z-scored. The baseline for hospital-type fixed effects is Public Specialist. Column (2) uses instruments. Columns (3)–(4) allow random coefficients. Column (4) additionally matches micro moments from NHMS survey data.

Figure C.1: Binscatter of Expected Profits in 1996 by District Characteristics



Notes: These binscatter plots show how expected profits estimated from the BLP demand estimates vary by district characteristics as a form of robustness check. The top left panel shows the relationship between expected profits and the proportion of college educated individuals in the district. Top right shows against population, top left against the Chinese population (the ethnic group that is most likely to seek private health care) and bottom right against rural population.

C.4 First-Stage CCP and Transition Estimates

C.5 CCP of Private Entry

Table **??** reports the logit for the conditional choice probability of private entry, estimated on the state vector $(n_{dt}^{\text{priv}}, n_{dt}^{\text{pubS}}, n_{dt}^{\text{pubNS}}, \log \text{pop}_{dt}, \text{doc\_bin}_{dt})$. Doctor stock enters flexibly via quintile dummies (bin $= 0$ for zero doctors, bins 1–5 for positive-stock quintiles). Standard errors are clustered at the district level.

Table C.4: CCP of Private Entry (Logit and Marginal Effects, District-clustered SEs)

	Logit Coefficients		Marginal Effects (dy/dx)	
	Estimate	Std. Error	Estimate	Std. Error
Doctor-stock quintiles (baseline = Q2)				
Q1	0.704	0.524	0.021	0.015
Q3	0.707	0.500	0.021	0.014
Q4	0.497	0.565	0.014	0.017
Q5	0.936	0.568	0.031	0.018
n^{pubS}	−0.306	0.118	−0.010	0.004
n^{pubNS}	−0.690	0.200	−0.023	0.008
n^{priv}	−0.111	0.029	−0.004	0.001
log(Population)	2.335	0.306	0.078	0.012
Constant	−32.460	3.778		
Observations		1,615		
District clusters		95		
Pseudo R^2		0.314		

Notes: Dependent variable is an indicator for private entry in district d and year t. Regressors include doctor-stock quintile dummies (Q1–Q5, baseline Q2), counts of public specialist and non-specialist hospitals, incumbent private hospitals, and log population. Marginal effects are average partial effects on Pr(Entry). For factor levels, dy/dx is the discrete change from Q2. Standard errors are clustered by district.

C.6 Additional Tables and Figures on Model and Estimation

Table C.5: Top 10 Diagnoses in Private Hospitals (2013)

Rank	Diagnosis Code	Description	N Patients	Percent (%)
1	**O80**	**Normal Delivery**	**45,907**	**5.94**
2	A09	Diarrhoea and Gastroenteritis	30,673	3.97
3	A90	Dengue Fever	23,387	3.02
4	K29	Gastritis and Duodenitis	22,114	2.86
5	J18	Pneumonia	21,426	2.77
6	B34	Viral Infection of Unspecified Site	20,255	2.62
7	O82	Delivery by Elective C-Section	19,581	2.53
8	J20	Acute Bronchitis	12,601	1.63
9	M51	Intervertebral Disc Disorders	11,367	1.47
10	N20	Kidney Stone	11,151	1.44

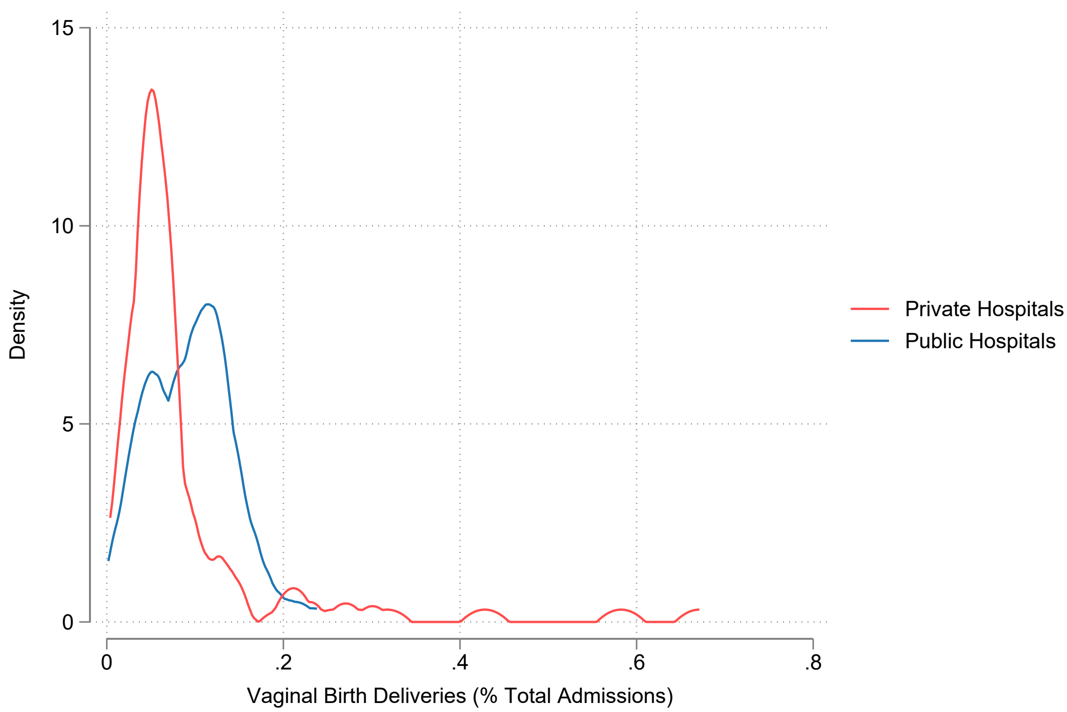
Notes: This table lists the top diagnoses in private hospitals with their corresponding ICD-10 codes, descriptions, patient counts, and percentages of total diagnoses.

Table C.6: Top 10 Diagnoses in Public Hospitals (2013)

Rank	Diagnosis Code	Description	N Patients	Percent (%)
1	**O80**	**Normal Delivery**	**176,582**	**10.66**
2	J18	Pneumonia	68,441	4.13
3	P59	Neonatal Jaundice	61,790	3.73
4	A90	Dengue Fever	37,787	2.28
5	A09	Diarrhoea and Gastroenteritis	35,743	2.16
6	O82	Delivery by Elective C-Section	30,927	1.87
7	J45	Asthma	27,512	1.66
8	E14	Unspecified Diabetes Mellitus	23,888	1.44
9	S06	Intracranial Injury	23,794	1.44
10	I20	Angina Pectoris	23,670	1.43

Notes: This table lists the top diagnoses in public hospitals with their corresponding ICD-10 codes, descriptions, patient counts, and percentages of total diagnoses.

Figure C.2: Birth Share Density

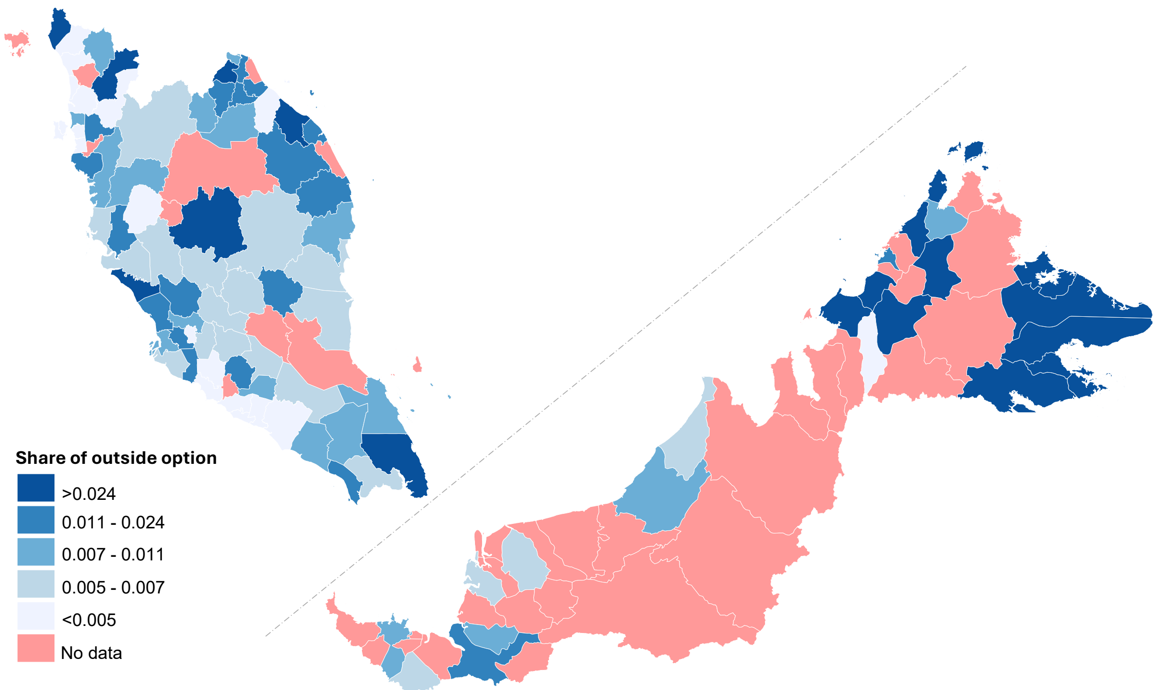


Notes: This figure shows the density of birth shares across public and private hospitals in Malaysia.

Figure C.3: Selected Maternity Package Posters

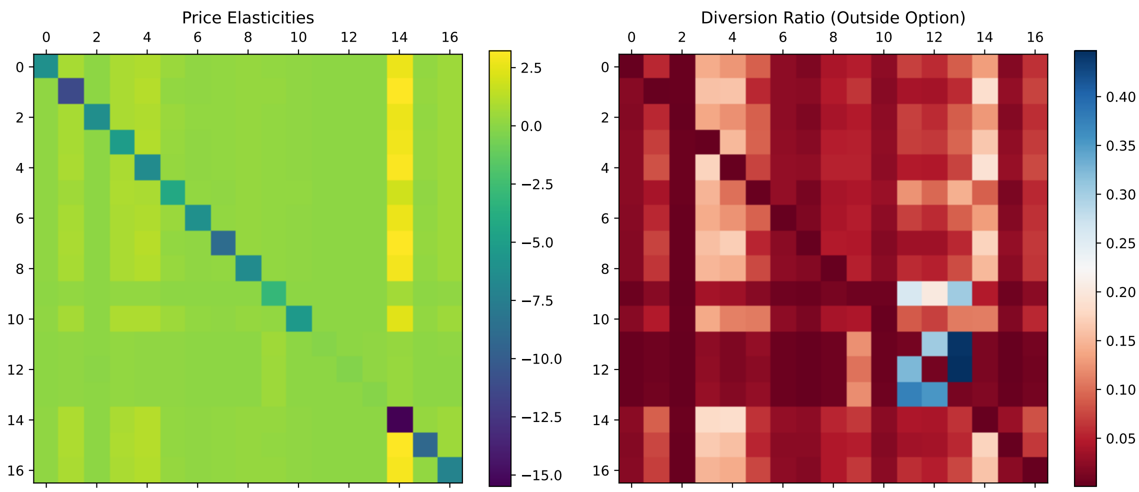
Notes: These posters advertise the maternity packages offered by private hospitals in Malaysia. The packages typically include prenatal care, delivery services (normal or C-section), postnatal care, and sometimes additional services such as ultrasounds or newborn care. Prices vary based on the hospital's location, reputation, and the specific services included in the package.

Figure C.4: Surveyed Districts and Share of Outside Option



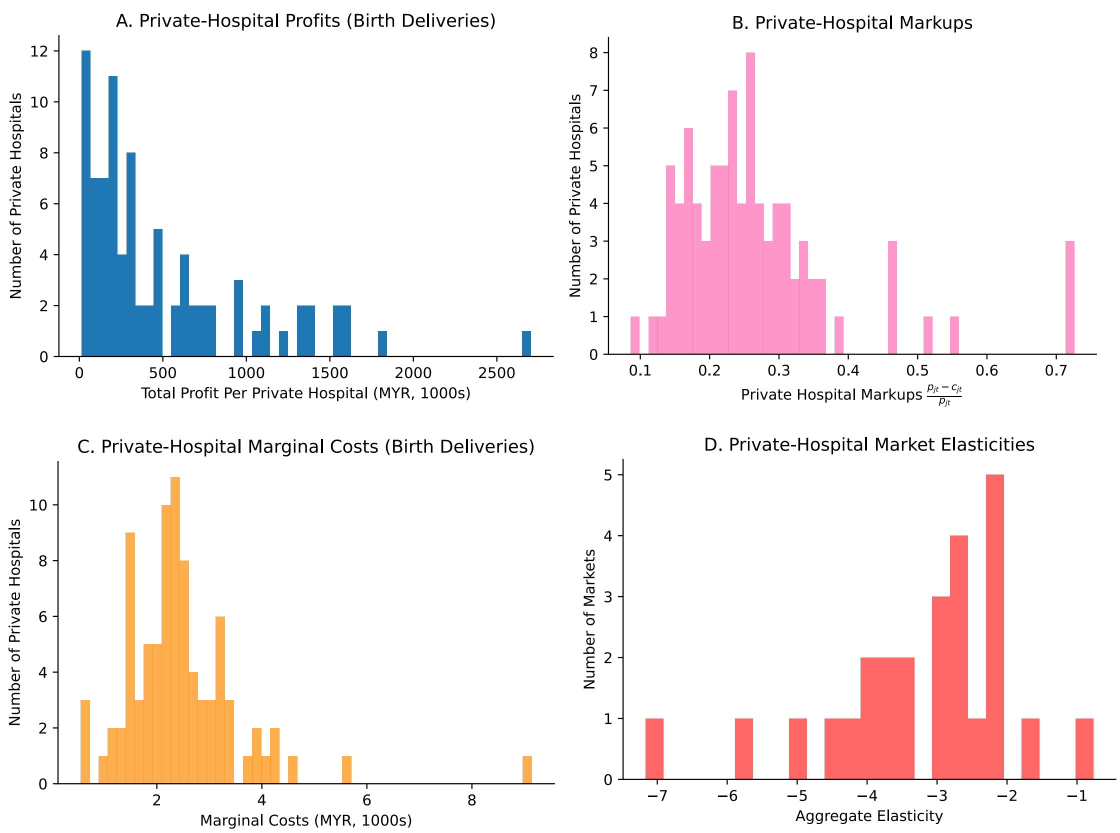
Notes: This map shows the surveyed districts in Malaysia and the share of the outside option (i.e., the proportion of patients seeking care in traditional/home births) for each district. Districts that are shaded pink are districts that were not surveyed and are omitted from the demand estimation.

Figure C.5: Estimated Price Elasticities and Diversion Ratios for the Kuala Lumpur District



Notes: Price elasticities $\varepsilon_{jk} = \frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k}$ measure the percentage change in market share of product k in response to a one percent change in the price of product j. Own-price elasticities (diagonal elements) are negative, while cross-price elasticities (off-diagonal) are typically positive. Diversion ratios $\mathscr{D}_{jk} = -\frac{\partial s_k}{\partial p_j} \Big/ \frac{\partial s_j}{\partial p_j}$ measure the proportion of consumers who switch from product j to product k when the price of product j increases. Diagonal elements show diversion to the outside good.

Figure C.6: Estimated Profits, Markups, and Elasticities



Notes: Hospital profits computed as $\pi_{ft} = \sum_{j \in J_{ft}} (p_{jt} - c_{jt}) s_{jt}$, representing total profits for ownership group f from all owned hospitals in market t. Markups derived from Bertrand first-order conditions as $\eta = p - c = \Delta^{-1} s$, where $\Delta = -\mathscr{H} \odot \frac{\partial s}{\partial p}'$ captures demand substitution patterns between hospitals under common ownership and $\mathscr{H}$ is the hospital ownership matrix. Marginal costs computed as $c = p - \eta$. Price elasticities $\varepsilon_{jk} = \frac{\partial s_k}{\partial p_j} \frac{p_j}{s_k}$ measure patient demand responsiveness to hospital price changes.