No Margins, No Mission: The Effects of Immigration on the Hospital Sector

Katharina Lewellen
Tuck School at Dartmouth
k.lewellen@dartmouth.edu

Giorgo Sertsios
University of Wisconsin Milwaukee
sertsios@uwm.edu

Jiadi Xu
University of Wisconsin Milwaukee
jiadixu@uwm.edu

September 2025

Abstract

We study the effects of immigration on the U.S. hospital sector. Instrumenting for immigration inflows using historical enclaves of foreign-born nationalities, we find that a 1% increase in immigration (relative to the county's initial population) leads to a 2.17% decline in hospital bed capacity over ten years. The effect is primarily driven by nonprofit hospitals, which are more likely to exit through closures or acquisitions. Continuing nonprofit hospitals experience a significant decline in their profit margins due to increased expenditure on uncompensated care. To cover the financial shortfalls, nonprofits curtail fixed-asset investments but do not raise additional funds. Our findings suggest that nonprofit hospitals operate under tight financing and operating constraints, limiting their ability to absorb profitability shocks and sustain their "mission-driven" objectives. In contrast, government-owned hospitals experience large losses but avoid exit and expand market shares.

* We thank comments and suggestions from Abhinav Gupta, Ethan Lewis, and seminar participants at The University of Alabama. We also thank Yusuf Raji for excellent research assistance.

1 Introduction

Immigrants accounted for over half of the U.S. population growth between 1965 and 2015, adding 72 million people to the total population, and the share is projected to increase in future decades.[1] This paper examines the effects of immigration on the U.S. hospital sector. This question is of interest at two levels. First, while immigration is a major driver of U.S. population growth, a disproportionate share of new immigrants lacks health insurance, thus posing challenges for the local healthcare sectors. Understanding how these sectors respond to this challenge is important from the public health and policy perspectives. Second, immigration waves provide a unique opportunity to study how U.S. hospitals make decisions and the constraints they face. We focus on nonprofit hospitals, which dominate the healthcare space but remain poorly understood. To contribute to this understanding, we apply a corporate finance framework to study how nonprofits respond to an immigration-induced economic shock.

The key challenge in estimating the effects of immigration is that immigrant flows are likely endogenous to the local economic conditions of the receiving country. For instance, if immigrants favor areas with stronger employment growth, we may observe a positive correlation between immigration and the growth of the local hospital sector. To address this challenge, the literature interested in the effects of migration relies on the fact that new immigrants tend to flow into their own nationalities' historical "enclaves." Geographic variation in the historical distribution of these enclaves across the U.S., combined with nation-wide immigration inflows into the U.S., can be used to construct valid instruments. As we explain in detail in Section 4, the hospital setting is especially well-suited for the application of the enclave instrument. We also show that our results are robust to a host of specifications and robustness checks, such as excluding any given county or the largest immigrant groups from the sample, using different measurement windows or weighting schemes in the regression analysis, and using alternative approaches to construct the instrument.

As a starting point, we examine the effects of immigration on the receiving county's local populations to understand better the mechanisms through which immigration might affect the healthcare sector. As expected, we find that immigration significantly increases the share of uninsured residents among a county's low-income population, and we find small but statistically insignificant

[1] Pew Research Center (2015).

declines in long-term native population growth.[2] These findings suggest two primary channels through which immigration may affect local hospitals: (i) "the uninsurance channels" operating via the increased share of uninsured residents, and (ii) "the demand channel" operating through a shift in the overall demand for healthcare services, for example, because new immigrants are initially healthier or less likely to seek healthcare services (as suggested in prior literature, which we summarize in Section 2).

Next, we examine how the hospital sector responds to immigration flows. We investigate all hospitals regardless of their organization form but focus on nonprofits as they account for over 60% of all U.S. hospital beds. The predicted responses in this group will depend on the assumed economic model of a nonprofit hospital. However, prior literature has proposed several such theories, modeling nonprofits as organizations that serve donors or taxpayers, pursue the interests of insiders, or simply maximize profits. Distinguishing among these theories has proven challenging, as nonprofits' actual behavior does not fit neatly into any single framework.

Our approach is instead to frame the analysis more broadly, starting with key accounting identities that must hold for every nonprofit in any given year. Doing so allows us to systematically track (and constrain) all possible ways in which a nonprofit hospital can respond to an economic shock. For instance, a hospital experiencing persistent losses caused in one part of its business must compensate by: (i) increasing profits elsewhere; (ii) soliciting additional donations or grants; (iii) increasing liabilities; or (4) reducing investment. If a hospital is unable to access these funding sources, it will eventually be forced to exit the market, either through a merger or closure. We examine the full range of possible responses to an immigration-induced economic shock, first analyzing the hospital sector as a whole and then samples of hospitals by organizational form.

We begin our empirical analysis on the county level, which is the smallest geographic unit for which we have immigration data. Thus, our unit of analysis in these regressions is a ten-year period by county, in line with the specification in the immigration literature. The first striking finding is that increased immigration flow into a county causes a significant shrinkage of the local hospital sector as measured, for example, by its total bed capacity. The effect is driven almost entirely by hospital exits, which include both mergers and closures. We find that an (instrumented) 1% increase in immigration flow over a ten-year period (measured as a percentage of the county's total population in the beginning

[2] These findings are broadly consistent with evidence in prior studies which report that, over a long run, some native workers tend to migrate away from high-immigration areas (see review in Card and Perri (2016)).

of the period) causes a 2.17% decline in hospital beds and a 2.12% decline in the numbers of hospitals. Because an average county experiences a 3.51% immigration flow over ten years, these estimates translate into a ten-year decline in both beds and a hospital counts of close to 7.5%. This represents a sizable effect, especially since immigration causes no long-term decline in the county's overall population.

When we decompose the estimated effects based on hospitals' organizational form, we discover that both effects are driven by nonprofits. While for-profit bed and hospital counts also decline, these effects are smaller and statistically insignificant. In contrast, public hospitals, which are funded directly from government budgets, expand their footprint and end up with significantly higher market shares. The combined effect is a significant shift in the ownership structure of the local healthcare sector away from private and towards public ownership. This shift counteracts the secular decline in public hospital ownership during our sample period (which we document in Figure 1).

To understand better the mechanism behind these effects, we turn next to hospital-level responses, starting with the hospitals' profitability. Hospital profits (i.e., net income) account for expenditure on uncompensated care, such as discounts offered to low-income patients or write-offs of unpaid bills. They also include revenue from new donations or government grants. Thus, finding no effect of immigration on profit margins would indicate that hospitals compensate for any reductions in profits (e.g., due to increased uncompensated care) either by increasing profits elsewhere or by securing additional donations or grants. We find that this is not the case for an average hospital. In fact, we find that immigration causes significant declines in hospitals' profit margins, and that much of this decline is caused by increases in uncompensated care.

When we decompose these effects by organization form, we find that the declines in margins and increases in uncompensated care are the largest for government hospitals, followed by nonprofit hospitals, with for-profits exhibiting no significant effects. For example, nonprofits experience a 0.4% decline in margins for each 1% increase in immigration. This translates into a ten-year decline in margins of 1.4% compared to average profit margin for nonprofits of 3.6%. We also find that these effects are heterogeneous: they are significantly stronger in the more populated counties, in which competition among hospitals is likely more intense.

The inability to fund the immigration-induced financial shortfalls from increased profits or contributions implies that nonprofit hospitals must resort to alternative sources of funds, such as borrowing or investment cuts. We find that scaling down investment was the dominant response,

possibly because raising debt would have been unsustainable in the long run. These effects are especially evident in the more populous metro counties: in these areas a 1% increase in immigration flows caused a 5.5% decline in fixed assets accompanied by a large reduction in fund balances (which are analogous to equity in for-profits) and a small and insignificant increase in liabilities. As a result, while hospitals avoided raising significant amounts of debt, their leverage ratios increased. These patterns are consistent with the increased hospital closures and takeovers (discussed earlier), which were likely preceded by financial and economic distress.

To summarize, the paper makes two main contributions. First, it shows that immigration flows have large and lasting effects on the local hospital markets, with the "uninsurance" channel playing a significant role. As immigration puts pressure on the hospitals' profit margins, some private (mostly nonprofit) hospitals exit, while public hospitals expand. The net effect is a reduction in the overall scale of the sector and a shift toward greater public ownership. Second, the paper provides insight into the economics of nonprofit hospitals. It shows that nonprofits respond strongly to the increased "need" for subsidized care in their local areas – similarly to public hospitals and unlike for-profits. However, compared to public hospitals, nonprofits have more limited funding sources available to support these additional needs, and they appear to face tight operating and financing constraints.[3] These findings underscore the strong link between the nonprofits' ability to generate profits and their capacity to pursue any other "mission-driven" objectives.

The paper contributes to three strands of the literature. First, extensive literature studies the effects of immigration on many aspects of the US economy, including labor markets, public finances, housing, productivity, innovation (see reviews in Lewis and Peri (2015) and Dustmann, Schönberg, and Stuhler (2016)). However, there is almost no research on the effects of immigration on the healthcare sector, with the existing studies (summarized in Section 2) focusing on health outcomes of immigrants, the immigrants' use of healthcare, and immigrants' insurance status. Our paper is the first comprehensive study of the impact of immigration on the hospital sector, examining both hospital-level responses, and the overall impact on the local healthcare systems.

The paper also contributes to the recent but growing area of healthcare finance. This literature examines various aspects of the healthcare sector, including hospital investments, the role of private

[3] This stands in a stark contrast to government hospitals who survive and even expand operations in spite of earning lower profits. Meanwhile, for-profits avoid losses, either by refusing to increase subsidized care or by adjusting more efficiently to the new demand.

equity, and nonprofit governance (Adelino, Lewellen, Sundaram (2015), Adelino, Lewellen, McCartney (2022), Aghamolla, Karaca-Mandic, Li, and Thakor (2024), Gupta, Howell, and Yannelis (2024), Gao, Lee, and Murphy (2022), Gao, Kim, Sevilir (2024), Cornaggia, Li, and Ye, and Lewellen, Phillips, and Sertsios (2023)). In particular, Gao, Lee and Murphy (2022) examine the effects of the introduction of the Affordable Care Act on the hospitals' cost of capital, while Cornaggia, Li, and Ye (2024) investigate the impact of telehealth technology on rural hospitals' financial health. Our paper explores an economically significant but localized shock that causes hospitals to experience persistent financial shortfalls. Using this shock, we trace the nonprofits' responses along multiple margins (including operations, investment, financing, and survival), thereby providing insight into these hospitals' objectives and constraints.

Finally, our paper contributes to the literature on hospitals' organizational forms in health economics (see reviews in Sloan (2000) and Gaynor, Ho, and Town (2015)). These papers typically do not examine corporate finance questions but instead focus on hospitals' operational efficiency, market structure, and medical choices.[4] The strand of the literature most closely related to our paper is the literature on "cost shifting," a practice whereby hospitals compensate for losses from Medicaid patients by increasing prices charged to private insurers. The literature finds limited evidence of such "dynamic" cost shifting, so our evidence is broadly consistent with their findings (see survey in Fract, 2011). Similarly, Garthwaite, Gross, and Notowidigdo (2018) show that increases in uncompensated care are associated with declines in profit margins for nonprofit hospitals, consistent with the hospitals' limited ability to cost shift.[5] To our knowledge, none of these studies examine the effects of immigration, and most studies focus more narrowly on pricing effects without exploring the full range of potential funding sources. Moreover, most cost-shifting studies examine samples from the 1980s and 1990s, which is when the major Medicaid cuts took place.

[4] The studies often compare the behavior of for-profit and nonprofit hospitals to test whether nonprofit choices align with their "softer" profit motives. The findings are generally mixed. For instance, Duggan (2000) examines hospital responses to a quasi-exogenous increase in financial incentives to treat low-income patients and finds that the responses were similar across the two organizational forms (see also Duggan (2002)). Silverman and Skinner (2003) find evidence of "upcoding" of patient diagnoses aimed at increasing Medicare reimbursement in both for-profits and nonprofits, with the former exhibiting larger effects (see also Dafny 2006)). Dranove, Garthwaite, and Ody (2017) examine hospital responses to the 2008 financial crisis and, again, find similar effects for nonprofits and for-profits (see also Adelino et al. (2015) and Adelino et al. (2022)). Duggan et al. (2023) show that privatizations of public hospitals are followed by increases in profitability and declines the quality of medical care.

[5] Garthwaite et al. (2018) also show that hospital closures are associated with increases in uncompensated care costs and declines in hospital profits in neighboring counties, suggesting causal effects of closures.

2 Background

2.1 Immigration and Healthcare

As of 2022, an estimated 46.2 million (13.9%) of the U.S. population was foreign-born.[6] This number increased steadily from 9.6 million (4.6%) in 1970. The U.S. Census does not collect data on the foreign-born residents' legal status, but according to the estimates by the Pew Research Center (PRC), approximately 23% of all immigrants are unauthorized, 45% are naturalized citizens, and the remaining 32% are permanent or temporary residents.[7] PRC estimates that, if current trends continue, immigrants, their children, and grandchildren will account for 88% of the U.S. population growth through 2065.[8]

While close to half of the foreign-born population comes from Latin America and the Caribbean, the flow of Hispanic immigrants has slowed over the recent decades. Since 2009, the number of immigrants arriving each year from Asia surpassed the number arriving from Latin America. Almost half of all foreign-born immigrants live in California, Florida, and Texas. Immigrants make up over 20% of the total population in five states (California, Florida, New Jersey, and New York), and they make up less than 10% of the population in 34 states.

Based on survey evidence, immigrants are less likely to have health insurance than the native-born citizens, and there are large differences in coverage across immigrant groups.[9] For example, Hamilton et al. (2022) report that, within immigrant population aged 19-64 during 2007-2008, the rates of coverage are lowest for unauthorized immigrants (34%) compared to 55% for legal permanent residents, 79% for naturalized citizens, and 77% for nonimmigrants.[10] The insured unauthorized immigrants rely primarily on private insurance (22%) and Medicaid (8%). The authors cite the lack of access to publicly funded insurance options (such as Medicare and Medicaid) and the more limited

[6] American Community Survey Briefs, 2024, The foreign-born population in the United States: 2022. https://www2.census.gov/library/publications/2024/demo/acsbr-019.pdf.

[7] Pew Research Center, 2020, Key findings about U.S. immigrants. https://www.pewresearch.org/short-reads/2020/08/20/key-findings-about-u-s-immigrants/, The methodology used in the estimation is described here: https://www.pewresearch.org/race-and-ethnicity/2018/11/27/unauthorized-immigration-estimate-methodology/.

[8] https://www.pewresearch.org/race-and-ethnicity/2015/09/28/modern-immigration-wave-brings-59-million-to-u-s-driving-population-growth-and-change-through-2065/

[9] Comparisons across immigrant groups are difficult because the U.S. Census surveys do not collect information on the respondents' immigration status. To overcome this challenge, researchers typically infer or impute leagal status based on the respondents' reported demographic and socioeconomic characteristics (see, survey in Hamilton et al. (2022)).

[10] The rates of uninsured among unauthorized immigrants are somewhat lower in the earlier studies that relied on alternative imputation methods. For example, Zuckerman, Waidmann, and Lawton (2011) report a rate of 57% and Fried et al. (2014) report a rate of 58%.

access to private insurance (because of working in jobs that do not come with health benefits) as the main reasons for the low rates of coverage among immigrants, especially those lacking legal status. Additional factors cited in the literature include confusion about access options, language barriers, and fear of accessing government funded programs (Kaiser Family Foundation, 2023)).

Immigrants can purchase private health insurance but, depending on their immigration status, they may not be eligible for government funded insurance programs. In general, unauthorized immigrants are not eligible for Medicare, Medicaid, CHIP, or plans available for purchase through the Health Insurance Exchanges under the Affordable Care Act (ACA). In addition, many otherwise qualified immigrants are prohibited from receiving Medicaid for the first five years since arrival (or since being granted legal status).[11] However, states can choose to offer coverage to immigrants that would otherwise not qualify for Medicaid or CHIP as long as they use state-only funds to finance it. Currently, six states (California, Colorado, Illinois, New York, Oregon, Washington) plus D.C. offer Medicaid coverage to low-income adults regardless of immigration status. Additional states offer limited coverage or restrict it to pregnant women or children.[12]

A large literature studies health outcomes of immigrant populations and shows that immigrants tend to be healthier than native-born citizens upon their arrival in the host country, but that this "health advantage" diminishes over time (see review in Cunningham et al. (2008) and NASEM (2015)). The studies cite lack of health insurance, along with behavioral changes, poor working conditions, and undiagnosed chronic conditions, as factors contributing to the decline (see, for example, Guintella and Mazzonna (2015)). The literature also finds that immigrants are less likely to use healthcare services than the native-born population, consistent with their better initial health status and lower rates of insurance coverage (Berk et al. (2000), Mohanty et al. (2005), Goldman et al. (2006)).[13] The lack of coverage implies that any health expenditures not covered out of pocket must be financed through other public or private sources, which we discuss in the next section.

[11] See details in Congretional Research Service (2022).
[12] See KFF Facts on Health coverage of Immigrants (September 17, 2023).
[13] Berk et al. (2000) report based on a survey evidence similar hospitalization rates but significantly lower rates of physician visits for undocumented Latino immigrants compared to the overall U.S. population. The rate of physician visits in the immingrant samples ranged from 27% in Los Angeles to 50% in Fresno compared to 66% for all Latinos and 75% for the U.S. population. Goldman et al. (2006) report similar results. Mohanty et al. (2005) estimate per capita healthcare expenditures for foreign born and native born populations and find substantially lower expenditures for the foreign born. Interestingly, these differences persist even within sub-samples of respondents with private or public health insurance.

2.2 Uninsured Patients: Access to Healthcare and Funding Sources

Uninsured patients, regardless of their immigration status, can obtain medical services through multiple channels, including emergency departments (EDs), hospital charity care programs, federally funded health centers, and privately funded free clinics.

Hospitals with EDs are required by federal law to provide health services to patients in emergency conditions regardless of the patients' ability to pay. After providing the stabilizing treatment, the patient may be admitted to the hospital or transferred to another hospital if further treatment is required. Hospitals can bill patients for their ED services but if a patient cannot (or does not) pay, the incurred cost becomes "uncompensated." Outside of EDs, uninsured patients can qualify for free or discounted hospital services as part of the hospitals' financial assistance programs (also known as "charity care"), which we discuss in more detail in Section 2.3. Coughlin et al. (2014) estimate that hospitals' total spending on uncompensated care – which includes charity care and funds written off as "bad debt" – was $44.6 billion in 2013.

In addition to hospitals, uninsured patients can access medical services through outpatient facilities known as Federally Qualified Health Centers (FQHCs). The vast majority of FQHCs are private nonprofit organizations funded by federal and local grants. The health centers are required to locate in "medically underserved" areas and offer discounts or waivers for low-income patients. While immigrants can receive care at any of the health centers, some centers specialize in services to migrant workers.[14] As of 2015, there were close to 9,500 health centers serving 24.1 million patients and accounting for $8.3 billion in federal or state grants.[15] A quarter of the centers' patients were uninsured and over two-thirds of the patients were classified as racial or ethnic minorities. Finally, uninsured patients, including immigrants, can receive care at privately funded free clinics. Similar to the health centers, the clinics specialize in primary care, referrals, and lab services. In 2023, there were 1,400 free clinics serving 1.7 million patients, 85% of whom were uninsured.[16]

Coughlin et al. (2014) estimate that total per capita medical spending for a full-year uninsured person was $2,443 in 2013, and that $500 of this amount was paid out of pocket. The remaining

[14] For instance, Family Health La Clinica in Wisconsin started as a health center focused on serving immigrant workers in the area under the name La Clinica de los Campesinos (https://nobleclinics.org/sobre-nosotros/).
[15] Of the $8.3 billion, $5.1 billion came from federal grants. See CRS Report R43937, Federal Health Centers, An Overview. Of the 9,500 health centers, approximately 1,300 are funded by the federal Health Resources and Services Administration (HRSA) Health Center Program.
[16] The National Association of Free & Charitable Clincs (2023).

(uncompensated) portion of this amount totaled between $79.9 and $89.9 billion, 65% of which was funded by governments, and the remainder was financed by philanthropy or profits from the privately insured. KFF (2021) estimates that after the implementation of the ACA, the uncompensated portion dropped to an average of $42.4 billion a year during 2015-2017.[17]

2.3 The U.S. Hospital Sector: Organizational Forms and the Provision of Charity Care

U.S. hospitals are organized as nonprofit, for-profit, or public (government owned) corporations, with nonprofits accounting for close to 60% of all hospital beds as of 2018. Figure 1 shows that this share remained stable throughout the sample period of 2000 to 2018. In contrast, the share of government hospitals declined from 27% to 21%, and the share of for-profit hospitals increased from 14% to 18%. These three types of hospitals differ significantly in their legal obligations to provide uncompensated care and in the government resources available to support such services.

All three types of hospitals (provided they have emergency departments) are required to offer emergency care to all patients, regardless of insurance status or ability to pay. Additionally, nonprofit hospitals must provide certain "community benefits" – including charity care – to maintain their tax-exempt status.[18] While this requirement does not extend to for-profit hospitals, some states mandate that all hospitals, including for-profits, provide a minimum level of charity care as a condition for licensing or participation in Certificate of Need (CON) programs.[19] Bruck and Bellamy (2020) find that, on average, for-profit hospitals allocate a similar fraction of their total expenses to charity care as nonprofits, a result consistent with estimates in our data (discussed below).

In contrast to private for-profit and nonprofit hospitals, public hospitals have a legal mandate to provide care to patients regardless of income or insurance status. Most public hospitals are owned and

[17] KFF (2021) Sources of payment for uncompensated care for the uninsured.

[18] See the IRS requirements here: https://www.irs.gov/charities-non-profits/financial-assistance-policy-and-emergency-medical-care-policy-section-501r4. The Affordable Care Act (ACA) imposed additional mandates on nonprofit hosptials, such as the requirement to have a written charity care policy, to identify and address local health needs every three years (see: ACA Section 9007).

[19] Currently, 35 states and Washington, D.C. operate Certificate of Need programs requiring hospitals to obtain state approval to conduct significant investments, such as expansions of facilities, acquisitions, or asset purchases. See: National Academy for State Health Policy (NASH), "50-State Scan of State Certificate-of-Need Programs" by Adney Rakotoniaina, Johanna Butler: https://nashp.org/state-tracker/50-state-scan-of-state-certificate-of-need-programs/. See additional discussion of state requirements regarding hospitls' charity care here: https://www.kff.org/health-costs/issue-brief/hospital-charity-care-how-it-works-and-why-it-matters/.

managed by state or local governments (counties or cities) and serve general populations.[20] A minority, such as Veterans Affairs (VA) or military hospitals, are owned by the federal government. Because these facilities serve specific groups, we exclude them from our sample in robustness tests. Public hospitals are funded directly through government budgets and can request additional funding as needs arise. Their other significant funding source is federal payments to providers serving disproportionately high shares of low-income or Medicare patients, known as Medicaid Disproportionate Share Hospital (DSH) payments and Medicare DSH adjustments. While nonprofit and for-profit hospitals may also qualify for these funds, eligibility criteria vary by state, and public hospitals often receive priority.[21]

In Section 5.4, we compare hospitals in our sample across the three organizational forms and show that, consistent with their ownership status, for-profit hospitals are the most profitable, followed by nonprofits and government hospitals. Conversely, government hospitals serve a disproportionately high fraction of low-income or uninsured patients, followed by nonprofits and for-profits.

3 Framework for Analyzing the Effects of Immigration on Nonprofit Hospitals

In this section, we provide a simple framework for thinking about how nonprofit hospitals might respond to a financial shortfall caused, for example, by an immigration shock. Unlike for-profits – whose choices are constrained by the value-maximizing motive – nonprofits' objectives are less well defined. It is not unusual for a nonprofit to formulate a broad mission (such as "to provide healthcare to the local community") without specifying its more concrete priorities, for example, how it views the trade-off between service quality and affordability, or what is its willingness to offer subsidized services to low-income patients.

[20] An example of a public hospital in our sample is Bellevue Hospital in NYC, part of NYC Health + Hospitals network operated under the authority of the New York City government. The system reports to the Mayor of New York City and is overseen by a Board of Directors, whose members are appointed by the Mayor, the New York City Council, and the Governor of New York. As of 2021, NYC Health + Hospitals served over 1.4 million people, including 475,000 uninsured city residents. The system advertises that it provides interpretation services in 190 languages. Another example is Memorial Hospital Miramar in Florida, part of the Memorial Healthcare System, a public system governed by the South Broward Hospital District Board of Commissioners. The district's major source of funding are property taxes levied within its boundaries. The Board of Commissioners is appointed by the Governor of Florida.

[21] See: Medicaid and CHIP Payment and Access Commission: "Improving the Targeting of Disproportionate Share Hospital Payments to Providers" (March 2017): https://www.macpac.gov/publication/improving-the-targeting-of-disproportionate-share-hospital-payments-to-providers/. See also: United States Government Accountability Office: "Medicaid: States' Use and Distribution of Supplemental Payments to Hospitals" (July 2019) https://www.gao.gov/products/gao-19-603.

However, a nonprofit's actual choices will depend on these (unobserved) priorities as well as on constraints stemming from the competitive market in which it operates. This paper examines a nonprofit's responses to a long-term economic shock (such as an increase in immigration). To constrain (and keep track of) the range of possible responses, it is helpful to consider the accounting identities that must hold for each nonprofit hospital in a given year:

$$A_t = L_t + FB_t \tag{1}$$

$$A_t = A_{t-\mathrm{x}} + \Delta Financial\ Assets_{t-\mathrm{x}} + \Delta Nonfinancial\ Assets_{t-\mathrm{x}} \tag{2}$$

$$L_t + FB_t = L_{t-\mathrm{x}} + FB_{t-\mathrm{x}} + \Delta L_t + Profit_t \tag{3}$$

$$Profit_t = Revenue_t - Cost_t - Uncompensated\ Care_t + Donations\ \&\ Grants_t \tag{4}$$

Equation (1) represents the basic balance sheet identity, stating simply that a nonprofit's assets must equal its liabilities and fund balances. Equations (2) and (3) describe the relation between the beginning-of-period and the end-of-period balance sheets, while Equation (4) defines a hospital's profits as including income from profitable services, funds spent on uncompensated care, and other income from donations and grants.

The economic shock we consider in this paper is a demographic shift due to an inflow of immigrant, and thus more often uninsured, population into the hospital's local area. One direct effect of this shift might be a change in the hospital's "optimal" scale. For instance, immigration may spur a decline in the overall demand for local healthcare services at prices that the hospital is willing to accept. If so, we would observe a reduction in the hospitals' assets, revenues, and investments. Prior literature, summarized in Section 2, suggests that this response is plausible because immigrants are initially healthier and younger than native residents, and that immigration may cause some native residents to migrate away in search of better job opportunities. [22]

The second direct effect of increased immigration will operate via the hospital's spending on uncompensated care. It is reasonable to assume that a nonprofit hospital will agree (or will be required) to provide some services to the new uninsured patients for free or at prices below marginal costs. If so, the nonprofit will experience a financial shortfall, reflected in Equation (4) as an increase

[22] These effects would be mitigated if immigration causes an overall increase in local population growth or if it encourages economic growth. We examine these effects in Section 6.1.

Uncompensated Care. Based on identities (1) – (4), the hospital will respond to this shortfall in one (or more) of the following four ways:

(1) Increase in $Donations\ \&\ Grants_t$. In principle, the additional "need" could be funded by an increase in contributions from donors or taxpayers who may derive utility from helping those in need. Whether or not such a response occurs depends on the donors' and taxpayers' willingness to provide the additional support as well as on the hospital's ability to access these funding sources. For example, it may be difficult for the hospital to convey the patients' needs credibly to potential donors (analogous to information frictions preventing firms from raising equity for good projects). It may be also difficult to overcome institutional frictions within a government bureaucracy (or within the democratic process) to access taxpayer funds.

(2) Increase in revenues or decrease in costs: $Revenue_t - Cost_t$. A hospital may be able to fund the shortfall by increasing profits in other parts of its business, for example, by raising prices or lowering service quality. If so, one might ask why the hospital did not take advantage of these profit opportunities before. One answer might be that a financial shock forced an inefficiently run hospital to cut waste or to negotiate with insurers. Alternatively, a hospital faced with an increased "community need" might choose to shift resources from other patients to the patients in need. It is important to note, however, that such a move may not be feasible for hospitals that lack pricing power or the ability to reduce quality without losing patients to competitors.

(3) Increase in liabilities ΔL_t. The hospital could also cover a financial shortfall, at least temporarily, by issuing debt, thus, effectively transferring resources from its future to its current patients. Note, however, that this adjustment is unsustainable in the long run: a hospital that issues debt year after year to cover losses will eventually risk financial default.

(4) Reduction in assets: ΔA_t, which include both financial and non-financial assets. A reduction in financial assets means that the hospital is investing in securities or building up cash balances at a lower rate than it otherwise would. A reduction in non-financial assets means that the hospital is investing in physical capital at a lower rate than it otherwise would. The latter response could indicate a more efficient use of assets or, alternatively, a reduction in the hospital's overall scale.

Identities (1) – (4) must hold for surviving hospitals. Note that a nonprofit hospital can survive a persistent financial shortfall, such as the shortfall due to increased immigration, as long as it has sufficient financial or operating slack to begin with. For example, prior to the shock the hospital might

have been using profits in ways that are not essential for survival, such as to accumulate financial assets, reduce liabilities, or expand operations. Alternatively, the hospital might have accepted lower profits to benefit patients, e.g., by maintaining service quality above the competitive level (or by maintaining prices below the competitive level). Finally, the hospital might have been poorly managed, with the shock forcing it to improve efficiency.

However, persistent financial shortfalls can also cause a nonprofit hospital to exit the market entirely.[23] A persistent failure to cover such shortfalls may jeopardize the hospital's ability to meet its financial obligations towards creditors, employees, or suppliers, eventually forcing an exit. In our data, we classify a hospital closure, a merger with another hospital, or an acquisition by (or a conversion into) a for-profit entity as a nonprofit exit. (Besides exits, we also examine hospital acquisitions by nonprofit systems whereby the hospital survives as a separate nonprofit entity though its control changes hands.) In the absence of frictions, exit through closures would occur if a hospital is worth less to its community as a going concern than the value of its assets when liquidated. Exit through a merger (or conversion) would occur if the hospital's assets can be managed more efficiently when they are combined with another nonprofit entity (or transferred to a for-profit entity).

It is worthwhile to note that an immigration shock could induce a nonprofit exit even if such an outcome is not desirable from the community's perspective. If a hospital was able to provide a net benefit to its community prior to the shock, then simply "allowing" the hospital to maintain its pre-shock status quo, i.e., by allowing it to refuse care to the additional uninsured patients, could be preferable to a liquidation (for example, in the sense that most community members would prefer this outcome). In practice, however, maintaining the status quo may not be feasible because hospitals are required to provide emergency services regardless of the patients' insurance status, or because hospital administrators may feel bound by the hospital's mission to extend financial assistance to patients in need.

4 Identification

Our main tests focus on the causal effects of immigration on real and financial outcomes of local hospitals outlined in Section 3. Estimating these effects is challenging because migration and healthcare are interrelated and can be affected by common underlying forces. As an example, consider

[23] An immigration shock could cause such a persistent shortfall by forcing the hospital to increase spending on uncompensated care (while hospitals may choose not to admit uninsured patients, they cannot refuse emergency care), or by reducing a hospital's revenue from insured patients if some of these patients migrate away.

a local productivity shock that attracts new migrants seeking job opportunities. Such shock could affect local hospitals by increasing demand for healthcare services (due to higher employment, income, and insurance coverage among the native population) or by improving hospitals' access to funding through local governments or private donations. As a result, we may observe a positive correlation between immigration and local hospital sector growth as both respond to the economic shock, masking any direct effects of migration flows.

To address this endogeneity problem, we rely on the instrumental variable approach developed by Card (2001, 2009) to study the effects of immigration on local labor markets. Their so-called 'enclave' instrument is a type of Bartik instrument that exploits the fact that historical concentrations of immigrants within geographic areas help predict future immigration into those areas. We show below that the methodology is well-suited for studying the effects of immigration on the healthcare sector, and that by adapting it, we are able to sidestep some of the challenges present in the labor-market context.

4.1 Baseline Regression

Our main tests are conducted at the county level. We focus on counties as the demand for healthcare is local, and counties are the finest level of aggregation for which we can identify both migration and hospital outcomes. The key explanatory variable measures the *flow* of new immigrants into county *c* between years *t-x* and *t*. Following prior literature, we scale the flow of recent immigrants by the location's population in *t-x* and denote this variable $X_{c,t}$. As a starting point, consider the following Ordinary Least Squares (OLS) regression:

$$Y_{c,t} = \beta X_{c,t} + \gamma W_{c,t-x} + \delta_{s,t} + \theta_m + \epsilon_{c,t}, \quad (5)$$

where $Y_{c,t}$ denotes a county-level outcome *flow* variable, such as the change in the number of hospitals or hospital beds from *t-x* to t scaled by the county's total number of hospitals or hospital beds in t-x; $W_{c,t-x}$ denotes a vector control variables at the beginning of the window, such as the log of county population, poverty rates, log of median household income, and county-level hospital characteristics, such as the log of the number of hospital beds by organizational form (government, nonprofit, and for-profit); $\delta_{s,t}$ are state-time period fixed effects that allow us to control for differential trajectories of counties within the same state and time window, for example, due to state-level regulations; θ_m are county-type fixed effects that capture heterogeneity related to a county's

location within or outside a Metropolitan Statistical Area (MSA), such as whether the county is central or peripheral within an MSA or located outside an MSA.

The specification allows for the inclusion of multiple time windows for each county in which case the data is a panel of within-county changes. The estimates help determine whether counties with higher immigration experience systematically different changes in hospital outcomes. While the regression includes a rich set of controls and fixed effects, some unobserved factors may still be omitted. As discussed above, one concern is that a positive economic shock could cause both higher immigration into the area and an expansion of the local healthcare sector.

4.2 Instrumental Variable

To address this concern, we construct an instrument for actual migration flows using predicted flows based on the historical distribution of immigrants across the U.S. The instrument exploits the fact that immigrants of a given nationality tend to move into areas where their nationality is more highly represented. For instance, during periods of increased immigration from the Dominican Republic, we would expect a disproportionately high fraction of new immigrants to settle in Bronx County, NY, a historical enclave for the Dominican community (according to the 2000 Census, residents born in the Dominican Republic accounted for 9.7% of all Bronx residents). Similarly, during periods of high immigration from China, we would expect especially high migration into San Francisco County, CA or Queens County, NY, both historically known as Chinese enclaves (based on the 2000 Census, 12.75% of San Francisco's population and 4.7% of Queens' population were born in China).

To capture this idea, we construct national 'enclaves' based on demographic information for a baseline Census year *h* (we use the 2000 Census for the main analysis). Thus, for each country of origin *f*, we compute the fraction of all foreign-born residents from that country that live in county *c*. We denote this fraction as $S_{c,f,h} = \frac{N_{c,f,h}}{M_{f,h}}$, with $N_{c,f,h}$ representing the number of residents from country *f* living in county *c*, and and $M_{f,h}$ representing the number of all residents from country *f* living in the U.S. Using this enclave information, we predict the net inflow rate of immigrants arriving in county *c* during a period of *t-x* to *t* as follows:

$$Z_{c,t} = \frac{\sum_f S_{c,f,h} * R_{f,t}}{P_{c,t-x}}, \tag{6}$$

where $R_{f,t}$ is the number of recent foreign nationals from country *f* relocating to the U.S. during *t-x* to *t* (for example, between the years 2005 and 2015), and $P_{c,t-x}$ is the total population of county *c* in year *t-x*. Thus, the instrument $Z_{c,t}$ is the predicted *flow* of immigrants into the county during a specified period expressed as a fraction of the county's population at the start of that period.[24] Equipped with this instrument, we estimate the effects of immigration on hospitals as follows:

$$X_{c,t} = \theta Z_{c,t} + \gamma W_{c,t-x} + \delta_{s,t} + \theta_m + \vartheta_{c,t} \quad (7)$$

$$Y_{c,t} = \beta \hat{X}_{c,t} + \gamma W_{c,t-x} + \delta_{s,t} + \theta_m + \omega_{c,t}. \quad (8)$$

The exclusion restriction requires $Z_{c,t}$ to be uncorrelated with $\epsilon_{c,t}$. As discussed in detail in Goldsmith-Pinkham et al. (2020), a violation of the exclusion restriction would occur if cross-sectional exposures, $S_{c,f,h}$, are correlated with future changes in the outcome of interest, $Y_{c,t}$, for reasons other than the causal effect of $X_{c,t}$. In other words, counties that are more prone to immigration from specific countries would need to experience systematically different hospital trajectories in periods in which total immigration from those countries is high. Figure 2 illustrates both the identification strategy and the exclusion restriction. We study the threats to identification in detail in Section 6.4.

5 Data and descriptive statistics

5.1 Data sources

Our primary source of the Census data is IPUMS USA (originally, the Integrated Public Use Microdata Series). The IPUMS database includes decennial censuses from 1790 through 2010 and the American Community Surveys (ACS) starting in 2000 to present. To construct historical enclaves, we use the 2000 decennial census (5% population sample) for the baseline analysis and the 1990 census for robustness tests. To construct migration inflows, we use the ACS data (1% population samples) for years 2005 through 2019.[25]

We obtain data on hospitals' organizational forms, system affiliations, and services from the American Hospital Association (AHA) Annual Survey Database. Information on hospitals' financials

[24] Appendix A describes how we construct immigration flows for the empirical analysis. Appendix B presents a numerical example for the instrument.

[25] We exclude earlier ACS data because they do not contain county identifiers. We limit the sample to years prior to the COVID-19 pandemic because of the pandemic's unprecedented effect on both hospitals and immigration.

comes from the Healthcare Cost Report Information System (HCRIS) and the Internal Revenue Service (IRS) Form 990s, which we obtain from the IRS website and Candid (formerly Guidestar).

We get data on health uninsurance rates at the county level from the Small Area Health Insurance Estimates (SAHIE) at the Census Bureau for years 2008 to 2019. We complement this information with data on uninsurance rates among patients of the Federally Qualified Healthcare Centers (FQHC) that receive funding from the federal Health Resources and Services Administration (HRSA). These clinics specialize in primary care outpatient services in otherwise underserved areas.

5.2 Descriptive evidence on immigration and implications for the instrument

This section describes key facts about immigration to the U.S. during our sample period. Appendix Figure A1 shows the percentage of foreign-born individuals living in the U.S. each year from 2005 through 2019. We classify a person as foreign-born (or immigrant) using the Census variable *Birthplace*, which identifies the respondent's country of birth.[26] Based on the figure, the share of immigrants in the total U.S. population increased steadily from 13.1% in 2005 to 14.6% in 2019.

Appendix Figures A2 through A5 illustrate immigration patterns by country of origin. Fig. A2 shows the top seven countries of origin for all foreign-born individuals living in the U.S. in our baseline year of 2000, while the subsequent three figures show immigration inflows from 2000 through 2019.[27] Overall, migration patterns have shifted considerably during our sample period. Based on Figure A2, Mexico was by far the most common country of origin in the early years, accounting for 28% of all foreign-born individuals living in the U.S. in 2000 (followed by China at 4.7% and the Philippines at 4.4%). However, based on immigration *flows* in Figure A3, other countries, like India and China, have closed in on Mexico regarding the inflow of immigrants in recent years. For instance, between 2000 and 2005, Mexico represented 34.8% of the inflow, followed by India and China with 5.2% and 4.6% respectively. However, between 2014 and 2019, Mexicans represented only 12.3% of the recent inflow of immigrants, closely followed by India (10%), China (8.4%), and other Latin American countries, especially those experiencing political turmoil, such as Guatemala and Venezuela. Figure A4 ranks the nations of origin by flows of migrants for our relevant windows of analyses: 2005-2015 to 2009-2019. Mexican-, Indian- and Chinese-born individuals represent the largest groups of recent immigrants.

[26] Birthplaces with fewer than 10,000 individuals or other ambiguous cases are grouped together as Other. This procedure results in 135 birthplaces in our sample.
[27] Based on the 2000 Census, the top seven countries represent 50% of the total foreign-born population in that year.

The dynamics of migration patterns illustrated in Figures A2-A4 suggest that the instrument is not driven by one dominant country of origin (such as Mexico) but rather reflects the combined effects of immigration flows from multiple countries into different locations over the 15-year sample period. In Section 6.4, we will show that the results do not rely on a single large nation for the identification of the effects.

5.3 Sample and descriptive statistics for the county-level analysis

The main sample for the county-level analysis consists of 326 counties and five overlapping ten-year periods, starting from 2005-2015 and ending with 2009-2019. We choose ten-year windows for the main analysis following Card (2009) and Goldsmith-Pinkham et al. (2020) to capture the long-term effects of immigration. We also provide evidence using shorter windows in Section 6.4. Our main analysis combines the five windows, so the regressions use all available data while smoothing any discrete changes between periods. Combining multiple overlapping 10-year windows has been possible only in recent years, as the ACS provides yearly county-level birthplace data since 2005.[28] The county window panel consists of 1,625 observations. We also report regressions for each of the five windows separately for robustness.

To be included in our sample, a county must have an identifier in the Census IPUMS data (which excludes small counties) and must have available data in the historical year, *h*, as well as in years *t-x* and *t* of the analysis window.[29] We also require counties to have at least one hospital in years *t* and *t-x*, which allows us to compute percentage changes in the number of hospitals or hospital beds (only two counties are dropped due to this restriction). In the main analysis, we consider all hospitals included in the AHA directory.[30]

Table 1 shows descriptive statistics for the county-level sample, focusing on the Census data. The stock variables reported in the table are as of year *t-x*, while the flow variables are changes from year

[28] While overlapping windows help smooth changes, they raise concerns about correlated standard errors across windows. In the empirical analysis, we address this by clustering at the MSA level (see Section 6 for further discussion)

[29] Not all counties have identifiers for the country of origin in the Census sample, and their availability varies over time. A county is identified in the sample if it was coterminous with a single Public Use Microdata Area (PUMA) or if it contained multiple PUMAs, none of which extended into other counties. As PUMA must have at least 100,0000 residents, only large counties are identified. Also, as PUMAs have been redrawn over time, some counties can be identified under some ACSs but not others. For example, Dane County in Wisconsin can be identified for all relevant years in our sample, but Milwaukee County (also in Wisconsin) can only be identified for a subset of years.

[30] In supplementary analysis, we exclude Military and Veterans' hospitals. This subset contains mostly military (e.g., department of the Navy), veteran, or specialty hospitals that are less likely to serve the immigrant population (see details in Section 2.3).

t-x to *t*. The average county in our sample has 513 thousand inhabitants, 11.27% of whom are foreign-born. On average, 15.77% of county residents under 65 are uninsured. This fraction rises to 29.76% (21.98%) for residents under 65 with incomes below 138% (400%) of the Federal Poverty Level (FLP). The table also reports the fraction of visits to the Federally Qualified Healthcare Centers (FQHCs) by patients classified as uninsured. These clinics specialize in primary care services in otherwise underserved areas and often target uninsured and immigrant populations (see Section 2.2 for additional background). Table 1 shows that 43.7% of the centers' patients in our sample report having no health insurance coverage.[31]

An average county experiences a ten-year inflow of recent immigrants equivalent to 3.51% of its total beginning-of-period population. The average predicted immigration is 2.79%, which is below the actual level. We find that this 'underprediction' is more common among smaller counties, which tend to grow their populations (including immigrant populations) at faster rates. When we weigh counties by their beginning-of-period populations, the predicted and actual immigration inflow increase to around 5% (Panel B), and the difference between them becomes negligible. To account for this, we weight the regressions by the beginning of the window population following the literature (e.g., Borjas (2006) and Card (2009)). We also control for county size in all regressions.

Appendix Figures A5 and A6 show the sample distributions by state and county type. The panel includes 37 states, with California being the largest and accounting for 170 county-periods and 10% of the sample. All states have at least two counties (or 10 observations considering all five windows per county), allowing us to introduce state-year fixed effects. We use the Census Bureau classification to group counties into five types based on their locations within or outside a Metropolitan Statistical Area (MSA). There are four within-MSA categories (e.g., Metro -area -central city; Metro area -Central mixed), and the fifth category are counties outside an MSA. Our regressions control for county-type fixed effects, allowing for differential trajectories in migration and hospital outcomes across county types.

Table 2, Panel A shows summary statistics for the county-level sample, focusing on hospital data from the AHA. The average county has 7.25 hospitals, 1,604 hospital beds, 68 thousand admissions,

[31] There are approximately 1,300 FQHCs funded by the federal Health Resources and Services Administration (HRSA) in operations per year nationwide, but many of the centers operate in small counties where foreign-born status cannot be identified in the Census data. We restrict our FQHC sample to counties used in our main county-level analysis that also have an FQHC. An average county in this sample has 2.2 centers providing close to 43,000 outpatient visits per year. In unreported results, we find that the uninsurance rates among FQHC patients decline by 17.35% during the period coinciding with the introduction of the Affordable Care Act (ACA).

1,106,000 outpatients, and 201,000 Emergency Room (E.R) visits per year. The average number of hospital beds per county is 342 (government), 998 (nonprofit), and 264 (for-profit). We use AHA classification to determine organizational forms.

Panel B of Table 2 shows that the number of hospital beds increased by an average of 1.69% per ten-year period. To better understand the change, we decompose the numerator by organizational form while keeping as the denominator to be the total number of hospital beds. This also allows us to keep the number of observations constant, as we do not require conditioning on the presence of any particular organizational form in a county at the beginning of the window. The table shows that the different organizational forms follow different trends during our sample period. Government hospitals experienced a decline equivalent to 3% of the county's total number of hospital beds at the beginning-of-the-window. In contrast nonprofits experienced a slight increase equivalent to 0.79% of a county's total bed capacity and for-profits experienced a large increase equivalent to 3.88% of bed capacity. We find similar patterns when looking at changes in the number of hospitals. Across all reported metrics, private hospitals increased their market share during our sample period.

5.4 Sample and descriptive statistics for the hospital-level analysis

The sample for the hospital-level analysis consists of hospitals included in both the AHA and the HCRIS databases. We require that a hospital has nonmissing data in both *t* and *t-x* and that it retains its organizational form during this period. The sample is restricted to hospitals with nonmissing financial data, so many federally-funded government hospitals (predominantly veteran hospitals) are not included in this analysis, as they do not report to the CMS. The final sample consists of 1,798 hospitals (8,021 hospital-window observations). The sample with available data for uncompensated care is smaller because this data is available consistently only starting in 2011. Thus, for the analysis of uncompensated care, we use the shorter windows (spanning five years) and a panel of 5,269 hospital-window observations.

Table 3, Panels A and B, show descriptive statistics for the full hospital sample, while Panel C compares hospitals across organizational forms. As before, the stock variables are as of year *t-x,* and flow variables are changes from *t-x* to *t*. The fractions of nonprofit, for-profit, and government hospitals are 60%, 30%, and 10%, respectively. Several differences across the organizational forms are worth noting. First, for-profit hospitals are significantly smaller than either of the two other hospital types: an average for-profit hospital has 131 beds compared to 290 for a nonprofit hospital and 325

for a government hospital. Second, profit margins are lowest for government hospitals (0.8%), followed by nonprofits (3.7%), and for-profits (7.8%). Third, government hospitals have the highest percentage of Medicaid admissions at 29.2%, compared to 18.96% for nonprofits and 16.1% for for-profits, and they allocate the largest fractions of their total expenditures to uncompensated care (12.7% compared to 6.5% for nonprofits and 5.7% for for-profits). These patterns are consistent with the objectives typically associated with each organizational form.

6 The Response of the Healthcare Sector to Immigration: County-Level Evidence

We begin the analysis on the county level, which is the smallest geographic unit at which we observe immigration flows. Following prior literature on the effects of migration, we examine changes over ten-year windows, weighting each observation by the county's population in *t-x* (see, for example, Borjas (2006), Card (2009)). We report the unweighted results as a robustness test in Appendix C (see also Section 6.4). Standard errors are clustered at the MSA level, which accounts for within-county correlation across overlapping windows and cross-county correlation within MSAs.

6.1 The Effects of Immigration on County-Level Population and Uninsurance Rates

This section examines the long-term effects of immigration on a county's population to better understand the channels through which an immigration shock may affect the hospital sector. Our focus is on the county's native population, uninsurance rates, and household income, as shifts along these metrics would directly impact the local residents' demand for healthcare services.

Notably, demographic effects of immigration have been investigated extensively in prior literature, so our goal here is merely to examine these patterns in our data to facilitate the interpretation of our main results. For instance, a standard argument in labor economics is that an influx of immigrants will boost labor supply in the short run, putting downward pressure on wages. In the long run, labor markets will adjust to the initial shock: for instance, native workers who compete with immigrants for local jobs may migrate elsewhere in search of better employment opportunities (or may acquire different skills), thus, reducing the overall population growth and softening the longer-term impact on wages. Extensive research in labor economics tests these predictions and generally finds evidence supportive of the long-run labor market adjustments.[32]

[32] See reviews of this literature, for example, in Card and Peri (2016), Ottaviano and Peri (2012), Dustmann, Glitz, and Frattini (2008), and Borjas (2006).

In Table 4, we explore these effects in our sample and find results broadly consistent with prior literature. Column (1) of Table 4 shows results from our first-stage regression in Equation (7). Based on these results, our instrument strongly positively predicts immigration: a one percentage point increase in the instrumental variable translates into a 0.67 percentage point increase in the actual immigration, with the F-test of 162. Column (2) presents results from the second-stage regression in Equation (8) of the change in the county's native population on the instrumented immigration flows. The coefficient of -0.34 suggests that immigration causes a net outflow of natives from the local area, but the effect is not statistically significant. The magnitude of -0.34 (suggesting that a inflow of a hundred new immigrants is offset by a net outflow of 34 natives) is broadly consistent with estimates in Borja (2006) and Card and Peri (2016), who report effects ranging from -0.66 and -0.10.

Columns (3) to (6) of Table 4 explore the effects of immigration on the county's uninsurance rates. The dependent variables in columns (3) to (5) are ten-year changes in uninsurance rates for segments of the population below 65 split based on their income levels. The panel is limited to two ten-year windows of 2008-2018 and 2009-2019 due to the availability of insurance data. The regressions show that while immigration has no significant effect on the overall uninsurance rates, it does have a strong positive effect on uninsurance rates among the lower-income populations. A one-percentage point increase in foreign migration leads to a 0.32% increase in uninsurance rates for people below 138% of the FPL and a 0.12% increase for people below 400% of the FLP. These results are consistent with the estimates of uninsurance rates of foreign-born residents reported in prior literature (summarized in Section 2).

As additional evidence, in column (6), we estimate the effects of immigration on uninsurance rates among patients of the Federally Qualified Healthcare Centers (FQHCs), which specialize in serving low-income or uninsured populations and may, therefore, attract a disproportionately high share of newly immigrant uninsured residents. (Similar uninsurance data is not available for hospitals.) Consistently, we find that the estimated effect on uninsurance rates in this sample is the highest, reaching 1% of the centers' total patient population. Finally, the regressions in Table A1 in the Internet Appendix examine the effects of immigration on the county's median household income and poverty rate. Consistent with prior literature, we find that immigration leads to long-run improvements (rather than a deterioration) in these outcomes (see, for example, Peri 2012).

Overall, the results in Table 4 point to the "uninsurance channel" as an important driver behind the adverse effects of immigration on the local hospitals' finances and survival rates. These adverse

effects may have been reinforced by the overall drop in demand for healthcare, assuming that the new immigrants' demand is lower than that of the native residents who migrated elsewhere. On the other hand, the adverse effects of this "demand channel" may have been mitigated by overall improvements in local economies or population growth resulting from immigrant flows. In Section 6.2, we examine the combined effect of these forces on the local healthcare sector and explore the specific channels in more detail in Section 7.

6.2 The Effects of Immigration on the County-Level Bed Capacity and Hospital Counts

We now turn to examining the effects of immigration, and the resulting decline in the local insurance coverage, on the hospital sector. As we explain earlier, a direct consequence of an increased immigration is that local hospitals may be required – or may choose – to provide certain services to new uninsured patients for free or at subsidized rates, leading to financial shortfalls. Hospitals can cover these losses in various ways (discussed in detail in Section 3), but if alternative funding sources are insufficient, some may choose to liquidate assets or even shut down. These effects could be reinforced if local demand for healthcare services declines, for instance, because recent immigrants are healthier than the native residents who migrate away (see discussion in Sections 2.1 and 6.1)).

We begin the analysis of these adjustments by examining counties' overall hospital bed capacity. We focus on bed capacity first for three reasons: (i) Hospital beds represent a hospital's key revenue generating asset, so changes in bed counts are informative about hospitals' key investments, divestitures, or exits. Notably, this measure reflects not only investments in physical beds but also in the infrastructure needed to care for patients, such as medical staff and equipment – some of which may be fully captured on a hospital's balance sheet. (ii) Information on hospital beds is available for the most comprehensive sample of U.S. hospitals included in the AHA survey. In contrast, other measures of physical investments, which we examine below, are available for more limited samples of hospitals that also report to the CMS.[33] (iii) Hospital bed capacity directly captures the health sector's ability to care for patients and is therefore often cited as a key metric in the context of public health.

Our estimates are reported in Table 5, Panel A. The dependent variable in column (1) is the ten-year change in the county's total beds from *t-x* to *t* scaled by the total number of beds in *t-x*. In columns

[33] Federally funded government hospitals, and private specialty hospitals with no Medicare or Medicaid-related programs (e.g., some psychiatric hospitals) are not required to file cost reports with the HCRIS. In addition, the HCRIS bed count tends to be lower than the AHA bed count (on average, the HCRIS bed data count is 8% lower than the AHA bed data count for hospitals with bed data in both datasets).

(2) – (5), the dependent variables are changes in beds for government, nonprofit, for-profit, and all private (that is, for-profit and nonprofit combined) hospitals, with each change scaled by the total number of beds across all organizational forms in *t-x*. The key independent variable is the instrumented immigration inflow measured over the ten-year horizons in percent of the county's population in *t-x*. The regressions control for the county's characteristics, state-year fixed effects, and county-type fixed effects. Standard errors are clustered on the MSA level.

The key finding is that immigration inflow into a county causes a significant decline in the county's hospital bed capacity. The magnitude is large: based on column (1), a 1% increase in immigration (as a fraction of total population) leads to a 2.17% decline in the number of hospital beds. This effect is driven entirely by the nonprofit hospitals (column (3)), with government or for-profit hospitals exhibiting no significant changes.

The large magnitude of the response seems puzzling. A potential explanation might be that hospitals, when faced with the need to scale down capacity or reduce investment, are unable to make incremental adjustments, leading to significant investment cuts or, in some cases, closures. We examine this possibility in Panel B of Table 5. The dependent variables in these regressions are ten-year changes in the numbers of all hospitals in a county (column (1)) and changes in the numbers of hospitals split based on their organizational forms (columns (2) to (5)). Each change is scaled by the number of all hospitals in *t-x*, regardless of organizational form.

The results show that immigration causes significant declines in hospital counts, consistent with their more frequent exits: based on column (1), a 1% increase in immigration causes a statistically significant 2.12% decline in the overall number of hospitals, with nonprofit hospitals (in column (3)) experiencing a 1.87% decline. Based on column (4), the number of for-profit hospitals also declines though the effect is only 0.6% and is not statistically significant. Interestingly, the number of government hospitals increases by a significant 0.41%. This finding suggests that government hospitals can absorb additional demand without jeopardizing their survival. This increased demand may come from both newly arrived immigrant patients and from native patients — who are more likely to be insured — in areas where private hospitals have shut down.

To gain additional insight into the mechanisms behind these effects, in Panel C we decompose changes in hospital counts into those caused by exits versus entries. We define a hospital exit as an event whereby a hospital that operates in a county in the beginning of a ten-year period (i) no longer operates as a separate entity at the end of the period due to a closure or a merger, or (ii) it operates

under a different organizational form.[34] Conversely, hospital entries are defined as events whereby new hospitals are established or existing hospitals are converted from a different organizational form. The first two columns of Panel C show evidence of both increased exits and decreased entries though only the exit effect is statistically significant. The increased exits occur almost entirely in the nonprofit sector while the decreased entries occur in both nonprofit and for-profit sectors (the entry effects are not statistically significant). The effects on government hospitals are not statistically significant but both entries and exits have the opposite signs to those estimated for private hospitals, consistent with government hospitals expanding their footprint and picking up the additional demand.

Finally, Table 6 shows the OLS regression of county-level hospital outcomes on actual (rather than instrumented) immigration (Equation (5)). In contrast to the IV results in Table 5, the OLS regressions show no significant associations between immigration and the decline in the hospitals' bed capacity or hospital exits. The one effect that remains significant in the OLS specification is the increase in the government hospitals' counts. The differences between the OLS and the IV estimates are consistent with the OLS estimates being biased, likely due to the omitted factors discussed in Section 4. For example, a positive local economic shock may attract migration and also spur demand for healthcare services among the native (and thus more likely insured) population, thus biasing the OLS coefficients in Table 5 for private hospitals. This bias is less likely to affect government hospitals, which may respond less strongly to economic growth. These findings highlight the importance of accounting for endogeneity in studies of immigration and healthcare.

In sum, we find that immigration had a significant negative impact on hospitals' overall bed capacity, driven primarily by nonprofit hospitals exiting local markets. These results are consistent with two channels: (1) nonprofits responding to a negative demand shock (e.g., because new immigrants seek fewer services than local residents who migrated away); and (2) nonprofits responding to financial losses from increased uncompensated care (e.g., emergency care provided to the uninsured). Interestingly, our findings reveal significant adjustments along the extensive margin, suggesting that many affected nonprofits were unable to cover financial shortfalls by increasing profits, drawing down financial assets, or making incremental adjustments to their investment rates. This aligns with the idea that many nonprofits operate under tight budget constraints. Finally, we observe significant differences in how for-profit and government hospitals responded to the shock, largely in

[34] The second form of entry and exit is relevant only when we break down hospitals by organizational form (i.e., in columns 3-8 in Panel C).

line with their distinct stated objectives. We explore these adjustments in greater detail using hospital-level data in Section 7.

6.3 The Effects of Immigration on the Private versus Government Hospitals' Market Shares

The previous section shows that immigration causes private, mostly nonprofit, hospitals to exit the market, thus reducing these hospitals' overall bed capacity. There is also evidence that government hospitals expanded their footprint, likely taking on a disproportionate share of services to the uninsured, but also by picking up demand in areas where private hospitals have shut down. In this section, we examine how these different responses shifted market shares of public vs. private hospitals in their local markets.

The results are reported in Table 7. The table shows IV regression similar to those in Table 5, except that the dependent variables are changes in the private (that is, nonprofit and for-profit) hospitals' market shares. Market shares are measured using the private hospitals' shares of total beds, hospital counts, admissions, outpatient visits, or ER visits relative to all hospitals operating in a county (the variables are changes in those shares from *t-x* to *t*). The findings are consistent across the four specifications, showing sizable declines in private hospitals' market shares, with the effects being statistically significant in all but one regression. For example, based on column (3), a 1% increase in immigration (as a fraction of total population) decreases the fraction of hospital admissions to private hospitals (relative to admissions to all hospitals) by 0.73%. This effect is an insignificant 0.55% for outpatient visits (column (4)), and a significant 0.88% for ER visits (column (5)).

Interestingly, the effects for ER visits and inpatient visits are similar. This may seem puzzling since hospitals are legally required to treat ER patients regardless of their insurance status, but they are not required to admit them for inpatient stays. The finding is consistent with government hospitals stepping in to extend inpatient services to both insured and uninsured patients who cannot get care elsewhere, thus increasing the public sector's market shares.[35]

To summarize, we find that immigration has a significant long-term effect on the local hospital sector. Higher immigration decreases the share of privately-owned hospitals and increases the share of government-owned hospitals in the local market, thus counteracting the nationwide trends documented in Figure 1. The findings are consistent with the idea that recent immigrants, who often

[35] Appendix Table A2 shows that a 1% increase in immigration leads to an increase if 0.153% in government hospital admissions, though the effect is not statistically significant.

lack health insurance, increase local demand for subsidized healthcare, prompting governments to step in and meet this demand. The findings are also consistent with government hospitals attracting native patients in areas in which private hospitals have shut down. The result is a lasting shift of the local hospital sector away from private ownership and towards government ownership.

6.4 Instrument Balance and Robustness Tests

6.4.1 Instrument Balance

The main identification assumption in Equations (7) and (8) is that (conditional on control variables) the predicted migration flows, $Z_{c,t}$, are uncorrelated with outcomes, $Y_{c,t}$ other than via their effect on actual immigration. The exclusion restriction – or the assumption that the instrument is as good as randomly assigned – is untestable. However, we present auxiliary evidence consistent with this condition being satisfied.

An indication that an instrument satisfies "as-random" assignment is that it is uncorrelated with the initial distribution of outcomes or, in other words, that it is well balanced (as discussed in Atanassov and Black (2016) and Bennedsen, Nielsen, Perez-Gonzalez, and Wolfenzon (2007)). We test for instrument balance by regressing the numbers and the market shares of hospitals by organizational form in the year 2000 on the instrumental variable averaged across the five ten-year windows. The regressions control for demographic county characteristics (income, population, and poverty rates) and fixed effects, matching the specification in Table 4. The results, reported in Table 8, show that the instrument is only weakly correlated with hospital outcomes in the historical Census initial year, which is consistent with as-random assignment. The lack of significance is not due to low statistical power arising from the smaller sample size when looking at a single cross-section: we find that the key control variables are significant at conventional levels (these results are not reported). Moreover, the IV regressions estimated on single windows yield statistically significant results, as we show in the robustness checks section and Appendix C.

6.4.2 Robustness Tests

We perform many robustness checks, which we describe in detail in Appendix C. This section provides a brief summary. The additional tests demonstrate that our findings are robust (1) to excluding any given county, as discussed by Young (2022), suggesting that no single county is pivotal for the results; (2) to excluding each of the three largest immigrant groups (Mexican, Chinese, and Indians) from the calculation of both the instrument and the actual migration inflows (showing that

our results do not hinge on the migration patterns of any large group of foreign nationals); (3) when using unweighted regressions rather than population-weighted regressions; (4) when using 1990 as the historical Census enclave year in the calculation of the instrument rather than the year 2000; (5) when using different immigration flow measures; (6) when using the five ten-year windows separately; (7) when using five-year windows rather than ten-year windows; (8) when aggregating at the MSA level instead of the county level; (9) when excluding Military and Veteran's hospitals. (10) Finally, we show that our results are robust using alternative approaches to construct the instrument, such as that proposed by Burchardi et al. (2024).[36]

7 The Response of the Healthcare Sector to Immigration: Hospital-Level Outcomes

We now turn to the question of how individual hospitals responded to the increase in immigration, focusing on the surviving hospitals. Our earlier tests show that immigration had no statistically significant effect on the destination counties' native populations, but that it tilted these populations towards newly immigrant, and more often uninsured, residents. As we discuss in Section (3), this shift could have affected local hospitals by reducing the overall demand for healthcare in their areas and by increasing the "demand" for uncompensated care. This section examines the combined effect of these forces on the local hospitals' profitability, investment, and financing.

7.1 The Effects on Profit Margins and Spending on Uncompensated Care

We begin by examining the hospitals' profitability. In our baseline tests, we use profit margin as our main measure, defined as net income scaled by revenue. Net income, as reported in hospitals' statements of revenues, accounts for expenditure on uncompensated care, so an increase in uncompensated care would put direct downward pressure on profit margins.[37] Importantly, net income also includes revenue from contributions, such as government grants or private donations. Finding no effect of immigration on profit margins would suggest that hospitals were able to offset any immigration-induced losses by increasing their profits elsewhere, or by securing additional

[36] A direct application of the Burchardi et al. (2024) instrument is unsuitable in our context because their instrument loses power when the counties' scale is accounted for (see detailed discussion in Appendix C and Internet Appendix Table A8).
[37] Since an increase in uncompensated care would reduce profits by a larger percentage than it would reduce revenues, profit margins (the ratio of the two) would decline. As we explain in Section 2, uncompensated care includes services provided to low-income and uninsured patients who qualify for financial assistance and are often offered regardless of the patient's immigration status. It also includes the so-called 'bad debt,' which refers to expenses the hospital writes off due to a patient's unwillingness (or inability) to pay.

donations or government grants. Conversely, finding a negative effect would indicate that these sources were insufficient to cover the immigration-induced shortfalls.

We test these hypotheses in Table 9. Mirroring the county-level analysis, we examine both the ten-year and the five-year windows and require non-missing hospital data in both year *t* and *t-x*. We also require that the hospital's organizational form is unchanged during the examined horizon. Data on uncompensated care is available only starting in 2011, so we limit this part of the analysis to the five-year windows. In contrast to the county-level tests, regressions are unweighted because larger counties contribute more hospital observations.

The key finding is that immigration significantly reduced hospital profit margins, with the magnitudes of this effect being similar across measurement horizons. Based on column (2) in Panel A, a 1% increase in immigration leads to a decline in hospital margins by 0.30%. With an average ten-year immigration rate of 3.51% (Table 1), this suggests a total decline in margins of about 1.1% in 10 years. As a comparison, the average margin of a hospital in Table 3 is 4.64%, and the average ten-year change in margins of 0.01%.[38]

To help interpret these effects, column (3) repeats the IV regression in column (2) but uses the ten-year change in the share of Medicaid admissions on total admissions as the dependent variable. This regression is a placebo test in the sense that an increase in the share of Medicaid patients (e.g., caused by a local economic downturn) could also explain a decline in hospital profit margins and, additionally, it could indicate a broader economic downturn in the area. However, such an effect would be an unlikely consequence of increased immigration because undocumented or recent immigrants typically do not qualify for Medicaid. As predicted, we find that the effect of instrumented immigration on Medicaid is insignificant and close to zero, reinforcing our conclusion that the decline in profit margins we estimate in column (2) is caused by an immigration shock rather than a generic downturn that confounds with it.

Panel B of Table 9 repeats the analysis in Panel A using the five-year windows, which allows us to examine uncompensated care. We find that the magnitude of the key coefficient in the margins regression is similar to what we find in Panel A. Importantly, we find that the decline in margins can

[38] These estimates are large, but the magnitudes appear to be economically plausible. For example, the 0.32% decline in hospital margins would translate into a 0.33% decline in revenues holding costs constant. A decline in revenue without a change in cost would occur if a hospital replaces an insured patient with a patient who receives the same treatment for free.

be attributed to an increase in uncompensated care (column (4)), and as before, there is no significant effect on Medicaid (column (3)). These findings are again consistent with immigration being a major driver behind the decline in profit margins: as we discuss in Section 2, recent or undocumented immigrants are typically not eligible for Medicaid but may be eligible for financial aid or may end up with unpaid hospital bills in the event of a medical emergency.

Notably, we scale uncompensated care expenditures in column (4) by revenues to make the coefficient directly comparable to that of profit margin in column (2). The coefficient on uncompensated care of -0.65 is larger in absolute value than that on profit margin of -0.41, suggesting that hospitals partially offset the increase in uncompensated care expenditures by increasing profits elsewhere. However, in unreported tests, we find that the difference between these coefficients is not statistically different from zero. In the Internet Appendix Table A10, we test whether private donations or government grants helped offset the increased costs of uncompensated care for nonprofit hospitals. We find that this was not the case: neither private donations nor total contributions increased significantly as a result of the increased immigration flows.

In the remaining panels, we split hospitals by their organizational forms. The regressions in Panels C and D show that government hospitals experience the largest declines in profit margins, followed by nonprofit hospitals. Government hospitals also experience the largest increases in uncompensated care (Panel G). Interestingly, there is also some evidence of declines in Medicaid admissions. These findings are consistent with government hospitals taking on the largest share of the recent immigrant patients, who typically do not qualify for Medicaid. In contrast, there is no evidence that for-profit hospitals experience declines in profit margins (Panels C and D). Combined with the negative effects on for-profit bed capacity (documented in Table 5), this finding suggests that shareholder-owned hospitals exit (or avoid entering) economically unsustainable markets, or that they adapt their business models to remain profitable in those markets.

7.2 Nonprofit Hospitals' Funding Sources: Investment and Financing

The previous section shows that immigration causes significant deterioration in hospital profit margins, driven to a large extent by an increase in spending on uncompensated care. Hospitals do not seem to be able to compensate for the additional spending by becoming more profitable in other parts of their business or by raising donations or government grants. In this section, we investigate their alternative funding sources, focusing on nonprofit hospitals. As we discussed in Section 3, a persistent

decrease in profits means that smaller surpluses are retained from year to year. Since a nonprofit hospital cannot raise equity, this shortfall needs to be offset by a reduction in assets or an increase in liabilities. Note that the former response could be preferable if immigration reduces the overall demand for hospital services, which may prompt the hospital to scale down its size.

We explore these adjustments for an average nonprofit hospital but also allow for heterogeneous responses by exploring subsamples split on hospitals' system affiliation, geographic location, and size. This heterogeneity could be important: for instance, hospitals belonging to a system could in principle cover their losses using funds transferred from other system entities – an option not available to standalone hospitals. Such transfers would be recorded as increases in fund balances on the hospitals' balance sheets, thus offsetting declines from retained earnings.

The full-sample regressions are reported in Table 10, and the sub-sample regressions are in Tables 11 and Appendix Table A11. Table 10 shows that an average nonprofit hospital responded to the increased immigration-induced losses by both increasing liabilities and decreasing investments in fixed assets, with only the latter effect being statistically significant. Based on column (2), fixed assets declined by 1.8% for every 1% increase in immigration. Interestingly, the surviving nonprofits did not reduce their bed capacity. This is in line with our earlier conclusion that the county-level aggregate decline in bed capacity was driven almost entirely by nonprofit hospitals exits. To the extent that capital investments – which include investments in buildings and equipment – provide value to the hospital's current and future patients, our results imply that nonprofit hospitals transfer welfare from those patients to accommodate the increased demand for subsidized care.

Turning to the subsample results, we find evidence that hospitals' responses are heterogenous in ways that make economic sense. For instance, in the Appendix Table A11, Panel A, hospitals are split based on whether they belong to a system or are standalone. As predicted, system hospitals appear to have covered the immigration-induced decline in retained earnings by increasing their fund balances in other ways, possibly through transfers from affiliated system entities. Based on column (4), the overall change in fund balances over the ten-year period is positive (and insignificant) in spite of the lower profits. In contrast, standalone hospitals experienced declines in fund balances and increases in liabilities, though the effects are again statistically insignificant. Appendix Table A11, Panel B examines the heterogenous effects according to hospital size, based on assets. The results are similar across small and large hospitals, suggesting that hospital size is not a strong predictor of how hospitals respond to the immigration shock.

The most striking results are in Table 11, where we split hospitals based on their location in a more populous versus less populous county. We find that hospitals located in the more populous counties experience substantially larger declines in their profit margins due to immigration. As a result, these hospitals exhibit large and statistically significant declines in fund balances, total assets, and fixed assets. While their liabilities also increase, the combined effect is a significant increase in their leverage ratios. A potential explanation for these findings is that the more densely populated areas are characterized by more intense competition among local hospitals. Consistent with this conjecture, Appendix Table A12 shows that market concentration measured by the HHI index is 1500 in the more populous counties compared to 3900 in the less populous counties. Hospitals facing more competitive pressure may be less able to cover unexpected losses by raising prices or lowering service quality. They may also be less able to improve efficiency, assuming that competition forced them to operate more efficiently to begin with.[39]

Pinning down the precise mechanism behind the differential responses we document in Tables 11 and A11 is beyond the scope of this paper. The broader point is, however, that average effects, such as those reported in Table 10, may conceal important heterogeneity in how hospitals choose (or can) respond to an economic shock. Examining these differential responses in future research could offer additional valuable insights into the economics of a nonprofit hospital.

7.3 The effects on hospital acquisitions and closures

Our evidence thus far shows that increased immigration puts pressure on nonprofit hospitals' profitability, causing some hospitals to cut investment. Consistent with these findings, our county-level tests document an increased incidence of nonprofit hospitals' exits, either through closures, mergers, or conversions into for-profits. In this section, we provide more specific evidence on the M&A and closure events. The sample for this analysis is a ten-year period by hospital panel, similar to that in Table 11, with a few modifications. First, we obtain the acquisition and closure data from Lewellen et al. (2025), whose panel ends in 2018 and includes only nonprofit and for-profit hospitals with both assets and revenues of at least $1 million. Second, unlike in Table 11, we no longer require that the hospital preserves its organizational form throughout the measurement period (as this would

[39] However, the heterogeneous effects could also be caused by differences across counties in the "type" of immigrants that respond to the instrument. Our IV estimates represent the Local Average Treatment Effects (LATE) for the compliers population (that is, for the population that responds to the instrument). Thus, if, for instance, the densely populated metro counties attract a disproportionate share of uninsured immigrants, the effects on local hospitals in those counties could be stronger.

eliminate some acquisition events). By definition, for the closure analysis, we also drop the requirement that the hospital survives throughout the measurement period.

The regressions are reported in Table 12. The dependent variable equals one if the hospital is acquired by a system (Panel A) or when it closes (Panel B) during the ten years. In Panel A, we consider separately acquisitions by both for-profit or nonprofit systems (columns (2) to (4)), only nonprofit systems (columns (5) to (7)), and only for-profit systems (columns (8) to (10)). Within each group, the samples are further split into all targets, only nonprofit targets, and only for-profit targets.[40]

The key finding in Panel A is that, consistently with our earlier results, nonprofit hospitals experience an increased incidence of system acquisition events as a result of immigration, and that this increase is caused entirely by acquisitions by for-profit systems. For instance, based on column (9), a 1% increase in immigration causes a 2.3% increase in nonprofit acquisitions by for-profit systems. This compares to a baseline average frequency of for-profit acquisition events of 8% (6% if considering nonprofit targets only). Because acquisitions by for-profits typically lead to a conversion of the nonprofit hospital into for-profit, these events contribute to the increased incidence of nonprofit exits we estimate in Table 5.

Panel B shows that both nonprofit and for-profit hospitals are more likely to close as a result of immigration inflows, further contributing to the exits and bed capacity declines. A 1% increase in immigration causes a 0.6% increase in nonprofit closures and 0.7% increase in for-profit closures, compared to the baseline frequencies of 1.4% and 3.3%, respectively. In unreported regressions, we repeat the analysis in Panel B for hospital mergers and find that, exits via mergers increase for both nonprofits but not for-profits, with the effects being 0.4% and 0.6% (compared to baseline frequencies of 2.4% and 1.5%), though only the effects for nonprofits are statistically significant.

These findings reinforce our earlier conclusions and provide more specific evidence on how the hospital sector adapts to the immigration-induced economic shock. The comparison between nonprofits and for-profits is interesting: it shows that an increase in immigration poses a challenge to both organizational forms, but that their responses differ. While some for-profit hospitals shut down, a typical for-profit remains profitable and survives the ten-year period (it may be because for-profits limit subsidies they provide to the uninsured, or because they are better able to adapt to changes in

[40] Note that a hospital acquisition by a system typically means that the hospital survives as a separate entity, though its control passes on to the acquiring system's board of directors. In contrast, mergers and closures result in a dissolution of the hospital (though in the case of mergers, hospital beds may be transferred to and operated by the merged entity).

economic conditions). In some cases, for-profits step in as acquirers of struggling nonprofits, prompting conversions.

8 Conclusions

Immigration represents a major source of U.S. population growth and its effects are often concentrated in specific geographic areas. This paper examines the effects of immigration on the local hospital sectors. Understanding how immigration affects local hospitals is important from a public policy standpoint if, for instance, the overall quality of healthcare suffers as a result. Moreover, the immigration setting offers a unique opportunity to study the responses of nonprofit hospitals to a long-term economic shock. We focus on nonprofits both because they account for the majority of U.S. hospital beds, and because their objectives and constraints are generally less well understood.

To identify the effects of immigration, we use a methodology that has been extensively used in prior literature. It relies on the fact that new immigrants tend to favor areas where their own nationality is historically well represented – the so-called historical enclaves. Thus, country-level shocks that cause immigration waves into the U.S. but are unrelated to the U.S. enclaves' economic conditions can be used to instrument for immigration flows. Using this instrument, we study the effects of immigration on the local hospital sector, focusing first on the county-level effects and then examining hospital-level outcomes in more detail.

One of our key findings is that immigration causes a significant reduction in the local bed capacity, driven primarily by hospital exits. For instance, a 1% increase in immigration flow into a county (as a percent of the county's total population) decreases both the local bed capacity and the local hospital count by close to 2.2%. These effects are caused almost entirely by nonprofit hospital exits. Consistently, we show that immigration causes significant increases in both nonprofit hospital closures and acquisitions of nonprofits by for-profit systems. Interestingly, government hospitals increase their footprint in the high-immigration areas, causing an overall shift in hospital ownership against private and towards public ownership.

These effects are mirrored in the hospital-level data. We find that surviving nonprofit hospitals experience significant reductions in profit margins as a result of immigration flows, driven primarily by increases in uncompensated care. An average nonprofit hospital is unable to compensate for the resulting losses either by increasing profits elsewhere or soliciting additional donations or government grants. Instead, we find evidence that nonprofit hospitals reduce investments in fixed assets to fund

their financial shortfalls. The effects are especially strong in the more populous metro areas, in which the competition among local hospitals is generally more intense. This suggests that in these environments, nonprofit hospitals are less able to shift the increases in costs by raising prices, lowering quality, or improving efficiency.

To summarize, we show that immigration has a significant and lasting impact on the local healthcare sector – reducing its overall scale and shifting its ownership towards the public and against the private sector. By examining the mechanisms behind these shifts, the paper offers insights into the economics of U.S. hospitals, majority of which are organized as nonprofits. It shows that while nonprofit hospitals are more likely (than for-profits) to step in to fill an increased "need" for subsidized care, these organizations find it challenging to fund the resulting losses either from profits or external financing sources. As a consequence, nonprofits resort to investment cuts, conversions into for-profits, or closures. The findings highlight the importance of the profit-generating activities for the nonprofits' ability to fulfill their nonpecuniary goals.

9 References

Adelino, M., Lewellen, K. and Sundaram, A., 2015. Investment decisions of nonprofit firms: Evidence from hospitals. The Journal of Finance, 70(4), pp.1583-1628.

Adelino, M., Lewellen, K. and McCartney, W.B., 2022. Hospital financial health and clinical choices: evidence from the financial crisis. Management Science, 68(3), pp.2098-2119.

Aghamolla, C., Karaca-Mandic, P., Li, X. and Thakor, R.T., 2024. Merchants of death: The effect of credit supply shocks on hospital outcomes. American Economic Review, 114(11), pp.3623-3668.

Atanasov, V.A., and Black, B.S. 2016. Shock-based causal inference in corporate finance and accounting research. Critical Finance Review 5, 207-304

Bennedsen, M., K. Nielsen, F. Perez-Gonzalez, and D. Wolfenzon., 2007. Inside the Family Firm: The Role of Families in Succession and Performance. Quarterly Journal of Economics 122, 647-691.

Berk, Marc L., Claudia L. Schur, Leo R. Chavez, and Martin Frnakel, 2000. Health care use among undocumented Latino immigrants. Health Affairs, July/August 2000, 51-63.

Burchardi, K.B., Chaney, T. and Hassan, T.A., 2019. Migrants, ancestors, and foreign investments. The Review of Economic Studies, 86(4), pp.1448-1486.

Burchardi, K.B., Chaney, T., Hassan, T.A., Tarquinio, L. and Terry, S.J., 2024. Immigration, innovation, and growth. National Bureau of Economic Research (No. w27075).

Borjas, George. Native Internal Migration and the Labor Market Impact of Immigration, 2006. The Journal of Human Resources, Vol. 41, No. 2, pp. 221-258.

Borjas, George. Immigration Economics, 2014. Harvard University Press.

Borjas, George. We wanted workers: Unraveling the immigration narrative, 2016. WW Norton & Company.

Card, David. 2001. Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. Journal of Labor Economics: 19(1) 22-64.

Card, David. 2009. Immigration and Inequality. American Economic Review: 99(2) 1-21.

Card, David, and Giovanni Peri. 2016. Immigration Economics by George J. Borjas: A Review Essay. Journal of Economic Literature: 54 (4), 1333–49.

Cornaggia, K., Li, X. and Ye, Z., 2024. Financial Effects of Remote Product Delivery: Evidence from Hospitals. The Review of Financial Studies, 37(9), 2817-2854.

Cornaggia, J., Cornaggia, K. and Israelsen, R.D., 2025. Unauthorized Immigration and Local Government Finances. *Working paper*.

Coughlin, Teresa A., John Holahan, Kyle Caswell, and Megan McGrath, 2014. An Estimated $84.9 Billion In Uncompensated Care Was Provided In 2013; ACA Payment Cuts Could Challenge Providers. *Health Affairs* 2014, 807-814.

Cunningham S. Argeseanu, Julia D. Ruben, and K.M. Venkat Narayan, 2008. Health of foreign-born people in the United States: a review. Health Place. 2008 (4), 623-635.

Dafny, Leemore, S., 2005. How do hospitals respond to price changes? *American Economic Review* 95(5) 1525-1547.

Dranove, David, Craig Garthwaite, and Christopher Ody, 2017. How do nonprofits respond to negative

wealth shocks? The impact of the 2008 stock market collapse on hospitals. *RAND Journal of Economics*. 48, 485-525.

Duggan, Mark, 2000. Hospital ownership and public medical spending. *Quareterly Journal of Economics* 115(4), 1343-1373.

Duggan, Mark, 2002. Hospital market structure and the behavior of not-for-profit hospitals. *The RAND Journal of Economics* 33(3) 433-446.

Duggan, M., Gupta, A., Jackson, E. and Templeton, Z.S., 2023. The impact of privatization: Evidence from the hospital sector. National Bureau of Economic Research (No. w30824).

Dustmann Christian, Albrecht Glitz, Tommaso Frattini, 2008. The labour market impact of immigration, Oxford Review of Economic Policy, Volume 24, Issue 3, Pages 477–494.

Dustmann, C., Schönberg, U., & Stuhler, J, 2016. The impact of immigration: Why do studies reach such different results?. Journal of Economic Perspectives, 30(4), 31-56.

Fried Brett, Jessie Kemmrick Pintor, Peter Graven, and Lynn A. Blewett., 2014. Implementing federal health reform in the States: who is included and excluded and what are their characteristics? Health Services Research 49 (S2), 2062-2085.

Garthwaite, Craig, Tal Gross, and Matthew J. Notowidigdo. 2018. Hospitals as insurers of last resort. American Economic Journal: Applied Economics 10 (1): 1–39**.**

Gaynor, M. and Vogt, W.B., 2003. Competition among hospitals. The Rand Journal of Economics, 34(4), pp.764-785.

Gaynor, M., Ho, K. and Town, R.J., 2015. The industrial organization of health-care markets. Journal of Economic Literature, 53(2), pp.235-284.

Gao, P., Lee, C. and Murphy, D., 2022. Good for your fiscal health? The effect of the Affordable Care Act on healthcare borrowing costs. Journal of Financial Economics, 145(2), pp.464-488.

Gao, J. Kim, S.K., and Merih Sevelir, 2025. Private equity in the hospital industry. *Working paper*.

Giuntella, Osea and Fabrizio Mazzonna, 2019, Sunset time and the economic effects of social jetlag: evidence from US time zone borders. Journal of Health Economics 65, 210-226.

Giuntella, Osea, and Fabrizio Mazzonna, 2015 "Do Immigrants Improve the Health of Natives?" Journal of Health Economics, 43 (2015), 140–153.

Goldman, Dana P., James P. Smith, and Neeraj Sood, 2006. Immigrants and the cost of medical care. Health Affairs 2006, 1700-1711.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H, 2020. Bartik instruments: What, when, why, and how. American Economic Review, 110(8), 2586-2624.

Gupta, A., Howell, S.T., Yannelis, C. and Gupta, A., 2024. Owner incentives and performance in healthcare: Private equity investment in nursing homes. The Review of Financial Studies, 37(4), pp.1029-1077.

Hamilton, Christal, Claire Altman, James D. Bachmeir, and Cody Spence, 2022. Legal status and health disparities: an examination of health insurance coverage among the foreign-born. Demographic Research 47, 453-488.

Jaeger, David, Joakim Ruist, and Jan Stuhler, 2018. Shift-share instruments and the impact of immigration. *Working paper*.

Jiang, Wei, 2017, Have instrumental variables brought us closer to the truth?, Review of Corporate Finance

Studies 6, 127-140

Lewis, Ethan G., and Giovanni Peri, 2015. Immigration and the Economy of Cities and Regions. Handbook of Regional and Urban Economics, Vol. 5, pp. 625–685.

Lewellen, K., G. Phillips, and G. Sertsios, 2025. Control Without Ownership: Governance of Nonprofit Hospitals. *Working paper*.

Medici, C., 2023. Closing Ranks: Organized Labor and immigration. *Working paper*.

Mohanty Sarita A., Steffie Woolhandler, David U. Himmelstein, Susmita Pati, Olveen Carrasquillo, David H., 2005. Health care expenditures of immigrants in the United States: a nationally representative analysis. American Journal of Public Health 95, 1431-1438.

Ottaviano, Gianmarco I. P. and Peri, Giovanni, 2012, Rethinking the effect of immigration on wages. Journal of the European Economic Association, 10: 152-197.

Peri, Giovanni, 2012 The effect of immigration on productivity: Evidence from US states. Review of Economics and Statistics 94, (1): 348-358.

Silverman, Elaine and Jonathan Skinner, 2004. Medicare upcoding and hospital ownership. *Journal of Health Economics* 23(2), 369-389.

Sloan, F.A., 2000. Not-for-profit ownership and hospital behavior. Handbook of health economics, 1, pp.1141-1174.

Young, Alwyn, 2022, Consistency without inference: Instrumental variables in practical application, European Economic Review, 147, 1-21.

Zimmerschied, Kyle. 2025. Should They Stay or Should They Go: Immigration and Municipal Bonds. Working paper.

Zuckerman, Stephen, Timothy A. Weidmann, and Emily Lawton, 2011. Undocumented immigrants, left out of health reform, likely to continue to grow as share of the uninsured. Health Affairs 30 (10), 1997-2004.

Appendix A: Variable definitions

Variables from the Census IPUMS database (County-level)

We use the Census variable "perwt" (person weight) to construct county-level numbers based on the IPUMS samples.

Immigrants (000)	Total number of foreign-born individuals (in thousands) who reside in county c.
Natives (000)	Total number of US-born individuals (in thousands) who reside in county c.
Population (000)	County population in thousands.
Immigrant (%)	Fraction of the total number of immigrants over the total population in county c.
Top 50 Metro Area.	Indicator variable that equals one for metropolitan areas with the 50 largest populations in 2005, and zero otherwise.
Imm. Inflow (%)	Ten-year immigration inflow into a county from *t-10* to *t* in percent of the county's population in *t-10* (in some tests, we use five-year inflows wherever indicated). Immigration inflow from *t-10* to *t* is the number of foreign-born people living in a U.S. county in year *t* who have not been living in the U.S in year *t-10*, i.e. for whom (t – immigration year) < 10. Immigration year is based on the Census variable "YRIMMIG."
Pred. Imm. Inflow (%)	Predicted ten-year immigration inflow, as described in Section 4.2 (in some tests, we use five-year flows wherever indicated). Country flows, $R_{f,t}$, are based on recent immigration in the last 10 years (i.e., year -immigration year <10). Historical Census, h, is the year 2000.
Mean Pred. Imm. Inflow (%)	Pred. Imm. inflow 10y (%) averaged over the five ten-year windows.

Variables from the SAIPE database (County-level)

Household Income ($000)	Median household income in thousands.
Poverty (%)	Fraction of the county residents living in poverty.

Variables from the Census SAHIE database (County-level)

Uninsured % (All income)	The percentage of a county's population below 65 years old without health insurance.
Uninsured % (<138% FPL)	The percentage of a county's population below 65 years old and 138% of the Federal Poverty Line without health insurance.
Uninsured % (<400% FPL)	The percentage of a county's population below 65 years old and 400% of the Federal Poverty Line without health insurance.

Variables from the Health Resources and Services Administration (HRSA) database (County-level)

FQHC Uninsured Visits	Number of uninsured visits to Federally Qualified Health Centers (FQHCs) in a county divided by the total number of visits to FQHCs in the county.

Variables from the AHA database (County-level)

% represents percentage terms relative to the county. Δ represents change over a ten or five-year window. Δ 'var'/ Beds (%) represents the change in 'var' scaled by the total number of county beds at the beginning of the window. Δ 'var'/ Hosp. (%) represents the change in 'var' scaled by the total number of county hospitals at the beginning of the window.

Beds	Total hospital beds in a county.
Gov Beds	Total government hospital beds in a county.
NP Beds	Total nonprofit hospital beds in a county.
FP Beds	Total for-profit hospital beds in a county.
Hospitals	Number of hospitals in a county.
GOV Hospitals	Number of government hospitals in a county.
NP Hospitals	Number of nonprofit hospitals in a county.
FP Hospitals	Number of for-profit hospitals in a county
Admissions (000)	Total hospital admissions in thousands.
ER visits (000)	Number of Emergency Room visits in thousands.
Outpatient visits (000)	Number of Outpatient visits in thousands.
Entries	Counts the number of hospitals (or hospitals of a given type) that enter a county between t and t-x, scaled by the total number of hospitals in t-x.
Exits	Counts the number of hospitals (or hospitals of a given type) that exit a county between t and t-x, scaled by the total number of hospitals in t-x.

Variables from the AHA database (Hospital-level)	
Δ represents change over a ten or five-year window. Growth rates for changes in levels are log('var')$_t$ -log('var')$_{t-x}$. Changes in ratios are 'var'$_t$-'var'$_{t-x}$. All within-hospital changes are winsorized at the 1% level.	
NP Hospital	Equals one for hospitals that operate as a nonprofit hospital.
FP Hospital	Equals one for hospitals that operate as a for-profit hospital.
GOV Hospital	Equals one for hospitals that operate as a government hospital.
Beds	Number of beds in a hospital.
Medicaid (%)	Fraction of Medicaid inpatient days to total inpatient days.
System	Indicator that takes a value of 1 if the hospital belongs to a hospital system.

Variables from the HCRIS database (Hospital-level)	
Δ represents change over a ten or five-year window. Growth rates for changes in levels are log('var')$_t$ -log('var')$_{t-x}$. Changes in ratios are 'var'$_t$ -'var'$_{t-x}$. All within-hospital changes are winsorized at the 1% level.	
Assets	Total assets (Worksheet G, Line 36).
Total revenue	The sum of net patient revenue and other revenue (Worksheet G, Lines 3 and 25).
Fixed assets	Total fixed assets (Worksheet G, Line 30).
Total liabilities	Total current and long-term liabilities (Worksheet G, Line 51).
Total Fund Balances	Total assets – total liabilities (Worksheet G, Line 59).
Margin (%)	Net income / Total revenue. Net Income comes from Worksheet G3, Line 29. Net Income does not consider depreciation or taxes, so it is comparable across organizational forms.
Uncompensated care (%)	(Cost of charity care and bad debt)/ Total revenue. The cost of charity care has been reported consistently since 2011 on Worksheet S-10, Line 23. Bad debt is reported on Worksheet S-10, Line 29. If the ratio is outside the [0,1] interval, it is assigned a missing value.
Donations (%)	Donations/ Total revenue. Donations are unrestricted contributions, donations, and bequests reported on Worksheet G-3, Line 24. If the ratio is outside the [0,1] interval, it is assigned a missing value.

Leverage (%)	Total liabilities/Total assets. If the ratio is outside the [0,1] interval, it is assigned a missing value.

Variables from the IRS 990 database (Hospital-level)	
Δ represents change over a 10 or five-year window. Changes in ratios are 'var'$_t$ -'var't$_{-x}$. All within-hospital changes are winsorized at the 1% level.	
Contributions (%)	(Contributions and grants)/ Total revenue. Contributions and grants are private donations and government grants (Part I, line 8). Total revenue includes program service revenue and all other revenue, including contributions and grants (Part I, line 12). If the ratio is outside the [0,1] interval, it is assigned a missing value.

System event variables (Hospital-level)	
The data from system events comes from Lewellen, Phillips, and Sertsios (2025). It is restricted to for-profit and nonprofit hospitals with (non-missing) assets and revenues above one million dollars annually. The data ends in 2018. The system event sample conditions on the hospital being present in the AHA dataset at both ends of the window (t and t-x), as hospitals acquired in system events continue to exist as separate entities. The closure sample only conditions on the hospital being present in t-x as it can drop out of the sample due to closures.	
Acquisition by FP or NP	Indicator that takes a value of 1 if a hospital was acquired by a for-profit or a nonprofit system in the ten-year window.
Acquisition by FP	Indicator that takes a value of 1 if a hospital was acquired by a for-profit system in the ten-year window. Hospitals with multiple acquisitions during a period are classified based on the organizational form of the first acquirer.
Acquisition by NP	Indicator that takes a value of 1 if a hospital was acquired by a nonprofit system in the ten-year window. Hospitals with multiple acquisitions during a period are classified based on the organizational form of the first acquirer.
Hospital Closure	Indicator that takes a value of 1 if a hospital closed during the ten-year window. Closures are obtained from the AHA database.

IIG instrument	
IIG instrument (000)	Predicted number of immigrants (in thousands) from Burchardi et al. (2019, 2024). Enclaves are based on predicted ancestry rather than birth nation. It is the predicted number of recent immigrants over five-year windows from 1980-2010 (unscaled). IIG stands for Immigration, Innovation, and Growth, which is the title of their 2024 paper.

Appendix B: Numerical Example for the Instrument

Suppose there are only two locations in the US: A and B. Consider the historical year, h, to be 2000. Suppose A has 10 million people and B had 1.6 million in 2000. Suppose only two foreign nationals live in these locations: F1 and F2. There were 4,000 people born in F1 living in location A and 6,000 in location B in 2000. There were 40,000 people born in F2 living in location A and 10,000 in location B. Hence, the share of F1-born immigrants (relative to the US total number of F1-born) in A was 40% (4,000/10,000), and 60% (6,000/10,000) in B in 2000. The share of F2 living in locations A and B was 80% (40,000/50,000) and 20% (10,000/50,000) relative to the overall population of F2 in the US, respectively. These shares represent $\mathbf{S}_{cfh}$.

Suppose we want to predict how many immigrants will relocate to A and B between 2005 and 2015. Suppose the recent migration inflow in the last 10 years of F1- and F2-foreign born between 2005 and 2015 is 50,000 and 500,000, respectively. The predicted migration of F1 to A is 20,000=(40%*50,000). The predicted migration of F2 to A is 400,000(=80%*500,000). The number of immigrants is expected to increase by 420,000 in A. Suppose A's population in 2005 was 15 million. Then, the predicted inflow rate $\mathbf{Z}_{A\text{-}2015}$ is 2.8%. The predicted migration of F1 to B is 30,000=(60%*50,000). The predicted migration of F2 to B is 100,000(=20%*500,000). Hence, the number of immigrants is expected to increase by 130,000 in B. If B's population in 2005 was 1.5 million, the net inflow rate $\mathbf{Z}_{B\text{-}2015}$ is 130,000/1,5000,000=8.7%.

Appendix C: Robustness Checks

1 P-value sensitivity

Several recent studies scrutinized the validity of IV estimates in different contexts (see, for example, Atanasov and Black (2016), Jiang (2017), and Young (2022)). For instance, Young (2022) shows that many IV setups are sensitive to small changes in the sample definition, such as removing one group of observations.

We examine the sensitivity of our findings to removing a particular county from the sample. Each county appears up to five times in the main regressions, corresponding to five ten-year windows. Thus, we estimate the second-stage regression of immigration on the change in the number of nonprofit hospital beds (scaled by the total number of beds at the beginning of the window) 326 times, excluding one county at a time (see Table 5, Panel A, column 3). We show the distribution of p-values and coefficient estimates in Figure A.7. The p-values never exceed 0.6%, and the coefficients range from -1.9 to -2.3. Hence, our results do not depend on extreme observations associated with a specific county.

2 Excluding large immigrant populations

We explore whether our main estimates are sensitive to the exclusion or inclusion of the three large immigrant groups during our sample period: Mexicans, Indians, and Chinese (Figure A4). To do so, we reconstruct the predicted and actual share of immigrants excluding each of these groups, one at a time. Table A.3 shows results obtained after excluding Mexicans, Chinese, and Indians, respectively. The key coefficients are similar across the three specifications, suggesting that none of the three major immigrant countries drive our results.

3 Unweigthed regressions

Following prior literature, our main estimates weight each location by its beginning-of-window populations (e.g., Borjas (2006) and Card (2009)). We now present the unweighted results in Table A.4, columns 1 and 2, and find similar results. Overall, our results are similar across different weighting schemes.

4 1990 Census as Historical Enclave Year

Our main estimates use the 2000 Census as the historical year to compute the distribution of immigrant enclaves. As the estimation windows shift from 2009-2019 to 2005-2015, the historical year becomes closer in time to the windows. As a robustness test, we re-estimate the main regressions using the 1990 Census as the historical year. Choosing the more distant historical year mitigates the concern that historical enclaves somehow predict future changes in hospital outcomes during the estimation windows (i.e., independently from their effects on future migration). Setting the historical year to 1990 increases the distance to the estimation windows to between 15 and 29 years, which makes such direct effects unlikely. The concern with this approach is, however, that earlier enclaves predict migration patterns less precisely, thus lowering the power of the instrument.

The regressions using the 1990 Census as the historical year are in Table A.4., columns 3-4. As expected, the first-stage regression is significantly weaker, with an F-test of 14.3. Yet, the magnitude of the main coefficients in column 4 is even larger than in the main tests in Table 5. Moreover, the coefficient remains significant at the 1% level. While the statistical power of the first-stage regression is weaker, the main results are similar, which mitigates concerns that omitted variables drive our results.

5 Different immigration flow measures

Our main analysis studies the effects of recent immigration on hospital outcomes, so our immigration measure focuses on foreign-born nationals that have moved to the U.S. within the past ten years (see Appendix A for variable definitions). We focus on recent immigrants because the effects of immigration on hospitals – through both the demand and the uninsurance channels – are likely most pronounced for this group. An alternative approach would be to study the effects of changes in the foreign-born population in a county, regardless of how long the foreign-born residents have lived in the U.S. The economics literature has taken both approaches, depending on the research question (see, e.g., Burchardi et al. (2019, 2024) and Card and Peri (2016)).

For completeness, we replicate our main county-level tests using the alternative approach and report the results in the Internet Appendix Table A4, columns (5) and (6). In these tests, immigration flow into a county during a ten-year period is measured as the change in the county's foreign-born population from t-10 to t, scaled by the county's total population in t-10 (we denote this quantity *Net Flow*). The *Net Flow* measure includes (in addition to recent immigrants) foreign nationals who have

been living in the U.S. prior to migrating into the county during the ten-year period and subtracts foreign-born nationals who moved out of the county during the ten-year period. The regression in column (5) of Table A4 shows that the power of the first-stage regression decreases when we use the *Net Flows* measure (compared to the main test in Table 4, column (1)). This is unsurprising, as the enclave instrument is better suited to predict immigration flows rather than relocations of foreign-born individuals previously living in the U.S. Despite the lower power, we still find that an increase in net immigration significantly decreases the nonprofit hospitals' bed capacity. Compared to the main regression in Table 5, Panel A, column (3), the coefficient is larger and remains statistically significant at the 1% level.

6 Separate event windows

Our main estimates use five overlapping windows (2005-2015 to 2009-2019) to examine the effects of immigration on changes in hospital outcomes. Combining the windows allows us to use all available data while smoothing any discrete changes in hospital outcomes or migration between windows. By clustering at the MSA, which nests individual counties in our data, we account for the autocorrelation in outcomes arising from overlapping windows.

Table A.5, presents the main regressions estimated separately for each of the ten-year windows. The coefficient for the change in the scaled number of nonprofit beds is always negative and significant at the 5% level at least. Note that the effect of immigration on the change in nonprofit bed capacity does not follow a monotonic pattern over the years: the coefficient is the highest in the 2005-2015 and 2009-2019 windows, and it is the lowest in the 2008-2018 window. Overall, the tests confirm that our results are not driven by a particular window.

7 Shorter windows

Our main estimates use five overlapping ten-year windows, which is consistent with prior literature examining the long-term effects of immigration. In this section, we explore the effects of immigration at a shorter five-year horizon. Table A.6 presents results from regressions estimated on ten five-year windows starting in 2005-2010 and ending in 2014-2019. The results are similar to those reported in Table 5 Panel A, suggesting that the hospital sector adapts quickly to the demand shocks caused by immigration.

The evidence in Table A.6 highlights another advantage of using the enclave instrument in the hospital setting. The instrument was originally developed to study labor markets, but the literature has struggled to interpret the findings because the different channels through which immigration affects employment or wages are difficult to isolate. For example, Jaeger et al. (2018) point out that immigration could suppress wages in the short run, but that lower labor costs would attract investment and, thus, raise wages in the long run. This is further complicated if local migration flows are positively correlated over time. These concerns are less applicable to our setting. Our goal is to estimate the net effect of immigration on the healthcare sector after accounting for the labor market adjustments, and there is no obvious reason to expect offsetting effects on hospitals at different horizons (we confirm this in Table A.6). Moreover, unlike in the earlier studies, the immigration patterns shift significantly during our sample period (as shown in Figure A3), which mitigates the concern that predicted migration captures the effects of past migration.

8 MSA-level Analysis

The literature has examined the local effects of immigration using historical enclaves at both the county and MSA levels, depending on the research question. Studies in labor economics have typically focused on MSA-level analyses, as labor markets often span larger geographic areas (e.g., Borjas, 2006; Card, 2009). In contrast, research on more localized outcomes—such as innovation, union membership, or local government finances—has primarily used county-level variation (e.g., Burchardi et al., 2024; Medici, 2024; Zimmerschied, 2025). Given that healthcare demand is more localized, particularly for uninsured patients seeking care through emergency rooms, our main analysis is conducted at the county level. However, for robustness, we also examine the effects of immigration at the MSA level.

In unreported results, we find that the hospital distribution at the MSA level closely mirrors that at the county level, and that both the first-stage regressions and the effects of immigration on demographic outcomes yield qualitatively similar results to those reported in the paper. Importantly, Table A.7 shows that the main effects of immigration on nonprofit beds and the total number of private beds remain robust. A 1% increase in immigration leads to a statistically significant 1.81% decline in the overall number of hospital beds, which is similar to the 2.12% decline estimated on the county-level (Table 5). One difference is that, at the MSA level, both nonprofit and for-profit hospitals experience significant declines in hospital beds, although the effect is more than twice as large for

nonprofits. Overall, our findings suggest that the negative impact of immigration on the nonprofit (and private) bed capacity persists at broader levels of aggregation.

9 Excluding Military and Veteran's Hospitals

Our main results are based on all hospitals included in both the AHA. Some of the government hospitals in the sample include veteran and military hospitals, which are less likely to serve recent immigrant populations. For robustness, we replicate the main results after excluding such hospitals. The resulting sample of government hospitals includes mostly locally funded government hospitals (i.e., county or state). Table A.8, Panel A shows summary statistics for the restricted sample. As expected, the average number of hospitals per county decreased from 7.25 in Table 2 Panel A to 7.02. Figure A8 replicates Figure 1 after excluding military and veterans hospitals. Using this restricted sample, we can see that the market share of government hospitals is lower than that of for-profit hospitals at the end of the sample.

Table A8 Panel B shows that our main results are robust to excluding federally-funded hospitals. This is to be expected as most of the effects are driven by nonprofit hospitals.

10 Alternative Instruments

Burchardi et al. (2019, 2024) modify the enclave shift-share instrument by instrumenting for the existing enclaves using information about historical immigration waves starting in 1880. They argue that if local productivity shocks are highly persistent, such shocks may affect both the initial immigration waves (and thus, the distribution of the historical enclaves) and the more recent immigration flows. Importantly, these distant shocks may also influence current local economic outcomes, such as innovation or growth.

This concern with the traditional enclave instrument is mitigated in our context for several reasons. First, persistent productivity shocks are unlikely to explain our finding that immigration has a negative effect on the local nonprofit hospitals' financial performance (if anything, we would expect positive productivity shocks to have a positive effect on hospital finances). Second, we show that the initial distribution of hospitals is unrelated to the predicted migration. If an underlying pre-existing productivity shock drives hospitals and immigration, the productivity shock should have affected the distribution of hospitals in the year 2000. Yet, we see that this is not the case (see Table 8). Third, we show that using the 1990 Census to determine historical enclaves does not affect our findings, so the

results appear robust to using information form a more distant past to construct the enclaves (see Internet Appendix Table A4). It is also worthwhile to note that the immigrant composition changed during our more recent sample period. For instance, the Mexican enclaves are the most relevant for constructing our instrument (Figure A2), but the recent immigration flows have shifted toward Asian immigrants (Figures A3 and A4). Moreover, we show that excluding each of the three largest immigrant groups does not affect the main findings (Internet Appendix Table A3).

Nevertheless, we perform additional robustness tests using Burchardi et al.'s (2024) instrument (Internet Appendix, Table A9). A direct application of their instrument is unsuitable for our context because we are interested in immigration flows relative to a county's population while Burchardi et al. (2019) examine unscaled immigration flows (that is, flows in thousands of people) and construct their instrument using absolute numbers of immigrants.[41] Therefore, in the Internet Appendix, Table A9, Panel A, we show for comparison results using both the original Burchardi et al. (2024) instrument (*IIG Instrument (000)*), and using their instrument scaled by the counties' populations (*IIG Instrument (%)*).[42] To match their specification, all regressions use five-year (rather than ten-year) periods.

Column (1) in Panel A shows that the Burchardi et al. (2024) instrument works well when used to predict unscaled immigration flows during their sample of 1980 to 2010. In column (2), we restrict the sample to the one five-year window that overlaps with our sample (2005-2010) and find that the instrument remains significant (with the F-test of over 70). However, the instrument loses power (with the F-test falling below 10) when immigration flows are scaled by the counties' populations, as shown in column (3). The power declines further in column (4) when we include county-type fixed effects and the full set of control variables we use in our main tests. Weighting the observations by the county's population does not significantly alter this finding, as shown in column (5). Based on this analysis, we conclude that using Burchardi et al.'s (2024) instrument is infeasible for predicting relative immigration flows in our sample.

However, to ensure that differences in specification do not drive our findings, we replicate our main tests using Burchardi et al.'s (2024) approach, that is, using absolute rather than relative immigration flows. In Table A9, Panel B, we use their instrument (unscaled) alongside our immigration

[41] We scale immigration inflows into a county by the county's population in *t-x*, which is also the standard approach in the literature (see, e.g., Card and Peri (2016)). Accounting for a county's scale is important in our setting: for instance, a relatively large number of immigrants in absolute terms may have a negligible effect on the patient population in the largest counties.

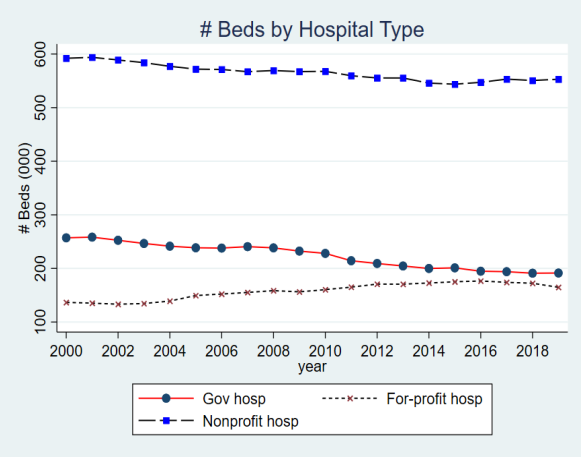
[42] IIG stands for Immigration, Innovation, and Growth, the title of their paper.

inflows (unscaled) for the only overlapping measurement window of 2005-2010. As expected, their instrument performs well when unscaled (column (1)). The results from the second-stage regression align with our main findings: a 1,000-person immigration inflow leads to a 1.2 bed reduction in nonprofit hospitals. Finally, for comparison, we repeat this test in Panel C using the standard enclave instrument, but unscaled. The results remain qualitatively similar and significant. Overall, our findings remain consistent across both approaches, reinforcing the robustness of our results.

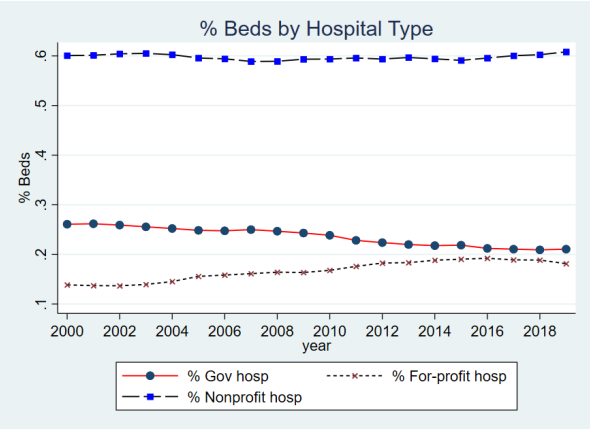
Figure 1: Hospital Beds over Time by Organizational Form

Panel A shows the total number of hospital beds by hospitals' organizational form reported in the AHA's Annual Survey Database from 2000 to 2019 (in thousands). Panel B shows market shares based on hospital beds of nonprofit, for-profit, and government hospitals by year (in percent). The right figure focuses on market shares of for-profit and government hospitals.

Panel A: Number of beds (in thousands) over time by organizational form



Panel B: Fractions of beds (in percent) over time by organizational form



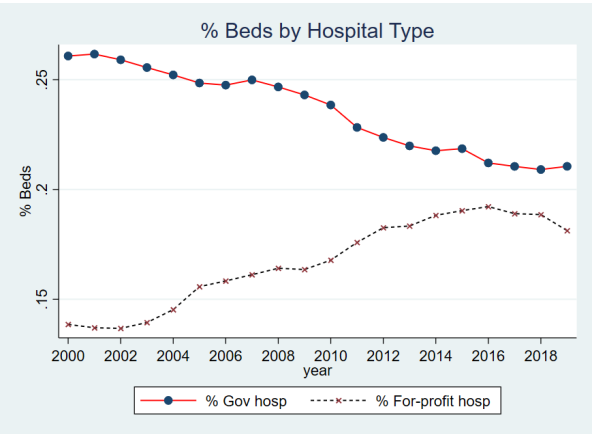


Figure 2: Identification Strategy

The figure summarizes the identification strategy for estimating the effects of immigration on the hospital sector. The notation is as follows: *h* stands for baseline Census year, *t-x* to *t* is the window of study, *f* stands for foreign country of origin, and *c* for county. For each country of origin *f*, we compute the fraction of all foreign-born residents living in county *c in year h*. We denote this fraction as $S_{c,f,h} = \frac{N_{c,f,h}}{M_{f,h}}$, with $N_{c,f,h}$ representing the number of residents from country *f* living in county *c*, and $M_{f,h}$ representing the number of all residents from country *f* living in the U.S. Using this enclave information, we predict the net inflow rate of immigrants arriving in county *c* during a period of *t-x* to *t* as $Z_{c,t} = \frac{\sum_f S_{c,f,h} * R_{f,t}}{P_{c,t-x}}$, where $R_{f,t}$ is the number of recent foreign nationals from country *f* relocating to the U.S. during *t-x* to *t* (for example, between the years 2005 and 2015), and $P_{c,t-x}$ is the total population of county *c* in year *t-x*. Thus, the instrument $Z_{c,t}$ is the predicted *flow* of immigrants into the county during a specified period expressed as a fraction of the county's population at the start of that period. The exclusion restriction implies that $S_{c,f,h}$ does not directly affect future changes in the outcomes of interests, $Y_{c,t}$.

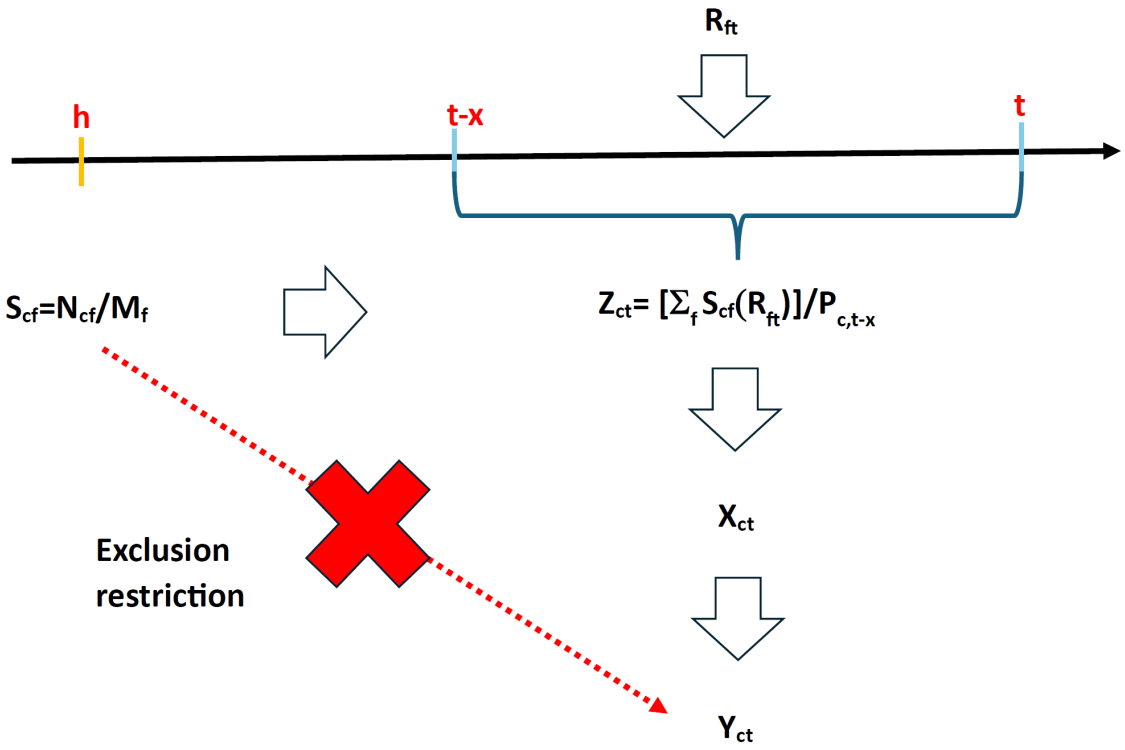


Table 1: Descriptive Statistics for County-Level Demographic Data

The table shows descriptive statistics for demographic data used in the county-level analysis. The main sample consists of a county-by-period panel that includes 326 counties and five ten-year periods from 2005-2015 to 2009-2019 (for *Uninsured %* we use two windows starting in 2008, the first year for which the data is available). Counties' demographic attributes are measured at the beginning of the ten-year periods (*t-10*); *Imm. Inflow (%)* measure changes in counties' immigrant populations from *t-10* to *t* scaled by the county's total population in *t-10*. Variable definitions are in Appendix A. In Panel A, observations are equal-weighted; in Panel B, they are weighted by the county's population in *t-10*.

Panel A: Counties are equal weighted

	Mean	P10	P50	P90	SD	N
Immigrants (000)	91.44	4.20	22.50	202.51	252.64	1,625
Population (000)	512.93	126.38	256.37	1,024.04	795.82	1,625
Household Income ($000)	53.09	38.58	50.26	73.13	13.63	1,625
Poverty (%)	12.27	6.10	11.74	18.58	5.10	1,625
Immigrants (%)	11.27	2.94	8.32	24.17	8.65	1,625
Top 50 Metro Area	0.49	0.00	0.00	1.00	0.50	1,625
Uninsured % (All income)	15.77	9.60	14.60	23.60	5.64	650
Uninsured % (<138% FPL)	29.76	21.00	28.80	40.35	7.20	650
Uninsured % (<400% FPL)	21.98	14.85	20.80	30.80	6.12	650
FQHC Uninsured Visits %	43.70	21.38	40.90	69.15	18.62	914
Imm. Inflow (%)	3.51	0.74	2.79	7.35	2.76	1,625
Pred. Imm. Inflow (%)	2.79	0.41	1.66	6.28	3.14	1,625

Panel B: Counties are weighted by their beginning-of-period population

	Mean	P10	P50	P90	SD	N
Immigrants (000)	461.70	12.35	143.08	1,076.11	845.01	1,625
Population (000)	1,746.60	185.07	877.29	4,023.49	2,355.83	1,625
Household Income ($000)	54.89	40.92	52.55	74.29	13.07	1,625
Poverty (%)	12.74	6.54	12.29	18.42	5.03	1,625
Immigrants (%)	17.83	5.11	16.68	35.89	10.89	1,625
Top 50 Metro Area	0.77	0.00	1.00	1.00	0.42	1,625
Uninsured % (All income)	17.20	10.10	16.70	24.90	5.96	650
Uninsured % (<138% FPL)	31.02	21.00	30.00	42.60	7.79	650
Uninsured % (<400% FPL)	24.07	16.00	23.50	32.40	6.60	650
FQHC Uninsured Visits %	47.20	23.96	46.38	71.61	18.14	914
Imm. Inflow (%)	5.03	1.64	4.31	9.50	2.99	1,625
Pred. Imm. Inflow (%)	5.08	1.00	3.90	11.58	4.18	1,625

Table 2: Descriptive Statistics for County-Level Hospital Data

The table shows descriptive statistics for hospital data used in the county-level analysis. The sample consists of a county-by-period panel that includes 326 counties and five ten-year periods from 2005-2015 to 2009-2019. Panel A shows county-level variables measured at the beginning of the ten-year periods (*t-10*). Panel B shows changes in the county-level variables measured from *t-10* to *t* constructed as follows: all changes in beds are scaled by total beds in *t-10*; all changes in the number of hospitals are scaled by the total number of hospitals in *t-10*. All changes are in percentages. Variable definitions are in Appendix A.

Panel A: Levels as of beginning of the measurement period

	Mean	P10	P50	P90	SD	N
Beds	1,604.24	221.00	742.00	4,005.00	2,486.26	1,625
GOV Beds	342.22	0.00	78.00	1,006.00	639.57	1,625
NP Beds	997.88	48.00	448.00	2,431.00	1,586.50	1,625
FP Beds	264.14	0.00	46.00	637.00	650.03	1,625
Hospitals	7.25	2.00	4.00	15.00	10.03	1,625
GOV Hospitals	1.20	0.00	1.00	3.00	1.74	1,625
NP Hospitals	3.83	1.00	2.00	8.00	5.31	1,625
FP Hospitals	2.22	0.00	1.00	5.00	4.69	1,625
% GOV Beds	18.52	0.00	8.42	55.13	24.62	1,625
% NP Beds	65.69	9.33	72.64	100.00	32.09	1,625
% FP Beds	15.78	0.00	4.03	47.40	24.10	1,625
Admissions (000)	67.72	10.56	30.37	172.57	105.82	1,625
Outpatient Visits (000)	1,105.76	160.66	550.36	2,718.19	1,613.94	1,625
ER Visits (000)	200.71	42.83	106.38	463.02	271.63	1,625
% Private Hospitals	83.13	50.00	89.47	100.00	21.94	1,625
% Private Admissions	86.80	59.52	98.23	100.00	23.25	1,625
% Private Outpatient Visits	80.63	36.62	99.88	100.00	27.63	1,625
% Private ER Visits	86.24	55.48	100.00	100.00	24.53	1,621

Table 2: Descriptive Statistics for County-Level Hospital Data, cont.

Panel B: Changes over the measurement period

	Mean	P10	P50	P90	SD	N
ΔBeds	-42.79	-385.00	-8.00	271.00	396.26	1,625
ΔGOV Beds	-55.92	-277.00	0.00	36.00	210.18	1,625
ΔNP Beds	-25.15	-312.00	0.00	235.00	317.71	1,625
ΔFP Beds	38.28	-60.00	0.00	198.00	195.93	1,625
ΔHospitals	-0.08	-2.00	0.00	2.00	1.77	1,625
ΔGOV Hospitals	-0.14	-1.00	0.00	0.00	0.55	1,625
ΔNP Hospitals	-0.17	-1.00	0.00	1.00	1.31	1,625
ΔFP Hospitals	0.23	-1.00	0.00	2.00	1.48	1,625
ΔBeds / Beds (%)	1.69	-30.10	-1.21	29.78	38.74	1,625
ΔGOV Beds / Beds (%)	-2.99	-17.59	0.00	2.85	23.41	1,625
ΔNP Beds / Beds (%)	0.79	-25.71	0.00	24.48	30.74	1,625
ΔFP Beds / Beds (%)	3.88	-5.03	0.00	18.65	17.59	1,625
ΔHospitals (%)	2.98	-25.00	0.00	33.33	31.92	1,625
ΔGOV Hospitals / Hosp. (%)	-2.53	-11.76	0.00	0.00	12.08	1,625
ΔNP Hospitals / Hosp. (%)	0.22	-24.00	0.00	25.00	22.12	1,625
ΔFP Hospitals / Hosp. (%)	5.29	-14.29	0.00	33.33	26.21	1,625
ΔPrivate Beds Share (%)	2.97	-3.06	0.00	14.50	13.89	1,625
ΔPrivate Hosp Share (%)	2.34	-2.38	0.00	10.71	12.49	1,625
ΔPrivate Adm. Share (%)	2.11	-2.98	0.00	7.17	13.83	1,625
ΔPrivate Outp. Share (%)	1.65	-8.94	0.00	11.28	15.49	1,621
ΔPrivate ER Share (%)	2.49	-2.78	0.00	9.47	14.33	1,619

Table 3: Descriptive Statistics for Hospital Data

The table shows descriptive statistics for hospital data used in the hospital-level analysis. The sample consists of a hospital-by-period panel that includes 1,798 hospitals and five ten-year periods from 2005-2015 to 2009-2019 (for *Uncompensated* we use five-year periods starting in 2011, the first year for which the data is available). Panel A shows hospital-level variables measured at the beginning of the period (*t-x*). Panel B shows changes in the hospital-level variables measured from *t-x* to *t*. All other variables in Panel B are changes in ratios from *t-x* to *t*. All changes are in percent. Panel C compares the hospital-level variables in *t-x* across organizational forms. Variable definitions are in Appendix A. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Panel A: Levels as of the beginning of the measurement period

	Mean	P10	P50	P90	SD	N
NP Hospital	0.60	0.00	1.00	1.00	0.49	8,021
FP Hospital	0.30	0.00	0.00	1.00	0.46	8,021
GOV Hospital	0.10	0.00	0.00	0.00	0.29	8,021
Beds	245.67	40.00	188.00	518.00	229.08	8,021
Medicaid (%)	19.08	4.38	16.95	36.51	14.62	8,021
Margin (%)	4.63	-6.19	4.37	17.26	10.36	7,688
Uncompensated (%)	6.92	1.86	5.50	12.70	6.26	5,262
Donations (%)	0.68	0.01	0.24	1.51	1.45	1,385
Contributions (%)	2.08	0.05	0.77	4.91	4.15	1,274
Leverage (%)	46.29	14.11	45.63	78.47	23.54	5,119

Panel B: Changes over the measurement period

	Mean	P10	P50	P90	SD	N
ΔMedicaid (%)	2.68	-8.46	2.75	14.54	12.11	8,021
ΔMargin (%)	0.01	-0.14	0.01	0.15	0.12	7,688
ΔLeverage (%)	-4.13	-33.69	-4.00	25.92	24.39	5,119
ΔDonation (%)	-0.02	-0.73	-0.03	0.68	1.35	1,385
ΔContribution (%)	-0.11	-2.49	-0.04	1.98	3.11	1,274
ΔUncompensated (%)	0.64	-4.84	0.22	6.26	4.89	5,262

Table 3: Descriptive Statistics for Hospital Data, cont.

Panel C: Comparison across organizational forms

	Means			Differences in Means		
	(1) GOV	(2) NP	(3) FP	(4) GOV-NP	(5) GOV-FP	(6) NP-FP
Beds	325.55	289.59	131.66	35.96*	193.89***	157.93***
Medicaid (%)	29.20	18.96	16.08	10.24***	13.12***	2.88***
Margin (%)	0.79	3.66	7.81	-2.87***	-7.02***	-4.14***
Uncomp. (%)	12.68	6.50	5.74	6.18***	6.94***	0.76
Leverage (%)	45.35	46.85	44.47	-1.49	0.88	2.38
ΔMedicaid (%)	1.40	3.82	0.80	-2.43**	0.60	3.03***
ΔMargin (%)	0.63	0.64	0.95	-0.01	-0.32	-0.31
ΔLeverage (%)	5.31	-4.683	-6.783	10.007***	12.108***	2.100
ΔUncomp.(%)	0.59	0.19	1.91	0.39	-1.32	-1.72***

Table 4: The Effects of Immigration on County-Level Demographic Outcomes

The table shows regressions of the county-level demographic outcomes on instrumented immigration flows. Column (1) shows the first-stage regression (Equation 7) of *Immigration Inflow (%)* from *t-10* to *t* scaled by the county's population in *t-10* on *Predicted Immigration Inflow (%)* over the same horizon. Columns (2) to (6) show regressions of the county's native inflow or changes in uninsurance rates on the instrumented immigration inflows (Equation 8). *Native Net Flow (%)* is the change in the county's native population from *t-10* to *t* scaled by the county's total population in *t-10*. *ΔUninsured (%)* is the change in the county's uninsurance rate from *t-10* to *t*. In columns (3) to (5), the uninsurance rates are for segments of population below 65 categorized based on their income levels relative to the Federal Poverty Level (FLP); in column (6) the uninsurance rate is for patients of the Federally Qualified Healthcare Centers (FQHCs). Control variables in columns (1) and (2) include *log(Population)*, *log(Household Income)*, *Poverty (%)*, *Top 50 Metro Area*, *log(FP Beds)*, *log(NP Beds)*, *log(GOV Beds)*, and *% Private Beds* in the county in *t-10*. An additional control in columns (3) to (6) is the uninsurance rate for the category of interest in *t-10* (for instance, in column (3), it is *Uninsured (%)* for *All Income*). Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dependent Var.:	Imm. Inflow (%)	Native Net Flow (%)	ΔUninsured (%)			
			All Income	<400% FPL	<138% FPL	FQHC Visits
	(1)	(2)	(3)	(4)	(5)	(6)
Imm. Inflow (%)		-0.341	0.047	0.121***	0.317***	1.001***
		(0.362)	(0.034)	(0.047)	(0.048)	(0.369)
Pred. Imm. Inflow (%)	0.674***					
	(0.053)					
Observations	1,625	1,625	650	650	650	914
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	1st	2nd	2nd	2nd	2nd	2nd
F test model	162.4					

Table 5: The Effects of Immigration on Hospital Capacity: County-Level Analysis

The table shows regressions of the county-level hospital outcomes on instrumented immigration flows. In Panel A, the dependent variables are changes from *t-10* to *t* in the number of hospital beds in a county categorized by the hospital's organizational form, with all changes being scaled by the total number of beds in the county in *t-10*. In Panel B, the dependent variables are changes from *t-10* to *t* in the numbers of hospitals categorized by organization form, with all changes being scaled by the total number of hospitals in the county in *t-10*. Panel C decomposes the changes in the numbers of hospitals into *Entries* and *Exits*. In columns (1) and (2), *Entries* (*Exits*) are numbers of hospitals that enter (exit) the sample from *t-10* to *t*, scaled by the total number of hospitals in the county in *t-10*. In columns (3) to (6) they are the numbers of hospitals of a given organizational form that enter (exit) the sample or change organizational form from *t-10* to *t,* scaled by the total number of hospitals in the county in *t-10*. Control variables in Panels B and C include those listed in Panel A and also include *log(GOV Hospitals)*, *log(NP Hospitals)*, *log(FP Hospitals)*, and *% Private Hospitals* in *t-10*. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Panel A: Dependent variables: changes in the number of beds in percent of total beds in t-10

Dep. Variables:	(1) ΔBeds / Beds (%)	(2) ΔGOV Beds / Beds (%)	(3) ΔNP Beds / Beds (%)	(4) ΔFP Beds / Beds (%)	(5) ΔPrivate Beds / Beds (%)
Imm. Inflow (%)	-2.172**	0.208	-2.172***	-0.208	-2.381***
	(1.004)	(0.369)	(0.538)	(0.539)	(0.908)
Log(Population)	3.031	1.086	2.347	-0.403	1.944
	(3.016)	(1.681)	(1.870)	(1.861)	(2.774)
Log(Household Inc.)	41.644**	0.373	42.361***	-1.090	41.271***
	(17.013)	(6.649)	(11.377)	(10.036)	(13.392)
Poverty (%)	0.681	-0.083	0.972*	-0.208	0.764
	(0.756)	(0.289)	(0.567)	(0.627)	(0.691)
Top 50 Metro Area	10.572**	-1.286	9.642**	2.215	11.857***
	(4.339)	(1.718)	(3.766)	(2.580)	(4.589)
Log(FP Beds)	-2.523***	0.023	-1.182*	-1.364**	-2.546***
	(0.797)	(0.232)	(0.618)	(0.539)	(0.796)
Log(NP Beds)	-1.968**	0.344	-2.548***	0.236	-2.311**
	(0.895)	(0.571)	(0.912)	(0.628)	(0.988)
Log(GOV Beds)	0.360	-0.182	0.219	0.324	0.543
	(0.926)	(0.483)	(0.676)	(0.601)	(0.849)
% Private Beds	26.195**	19.327**	2.135	4.732	6.868
	(11.220)	(8.983)	(10.482)	(7.140)	(11.547)
Observations	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd

Table 5: The Effects of Immigration on Hospital Capacity: County-Level Analysis, cont.

Panel B: Dependent variables: changes in the number of hospitals in percent of all hospitals in t-10

Dep. Variables:	(1) ΔHospitals / Hosp. (%)	(2) ΔGOV Hosp. / Hosp. (%)	(3) ΔNP Hosp. / Hosp. (%)	(4) ΔFP Hosp. / Hosp. (%)	(5) ΔPriv. Hosp. / Hosp. (%)
Imm. Inflow (%)	-2.121***	0.407*	-1.865**	-0.664	-2.529***
	(0.647)	(0.239)	(0.901)	(0.437)	(0.791)
Observations	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd

Panel C: Dep. variables: numbers of hospital entries (exits) from t-10 to t in percent of all hospitals in t-10

	All		GOV		NP		FP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Variables:	Entries	Exits	Entries	Exits	Entries	Exits	Entries	Exits
Imm. Inflow (%)	-0.824	1.297***	0.352	-0.056	-0.461	1.403**	-0.525	0.140
	(0.577)	(0.271)	(0.224)	(0.139)	(0.414)	(0.607)	(0.448)	(0.202)
Observations	1,625	1,625	1,625	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd	2nd	2nd	2nd

Table 6: OLS Regressions of Hospital Capacity: County-Level Analysis

The table replicates the results from Table 5, but using OLS (Equation 5) rather than the instrumental variable approach. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Panel A: Changes in beds by organizational form in percent or total beds in t-10

Dep. Variables:	(1) ΔBeds / Beds (%)	(2) ΔGOV Beds / Beds (%)	(3) ΔNP Beds / Beds (%)	(4) ΔFP Beds / Beds (%)	(5) ΔPrivate Beds / Beds (%)
Imm. Inflow (%)	0.053	0.581*	-0.608	0.079	-0.528
	(0.684)	(0.326)	(0.599)	(0.385)	(0.645)
Observations	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Panel B: Changes in the number of hospitals in percent or all hospitals in t-10

Dep. Variables:	ΔHospitals / Hosp. (%)	ΔGOV Hosp. / Hosp. (%)	ΔNP Hosp. / Hosp. (%)	ΔFP Hosp. / Hosp. (%)	ΔPriv. Hosp. / Hosp. (%)
Imm. Inflow (%)	-0.825	0.303*	-1.138	0.011	-1.128
	(0.694)	(0.160)	(0.738)	(0.373)	(0.781)
Observations	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Panel C: Numbers of hospital entries and exits from t-10 to t in percent of all hospitals in t-10

	All		GOV		NP		FP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Variables:	Entries	Exits	Entries	Exits	Entries	Exits	Entries	Exits
Imm. Inflow (%)	-0.009	0.816***	0.310**	0.007	-0.449	0.690	0.189	0.178
	(0.541)	(0.269)	(0.121)	(0.139)	(0.339)	(0.541)	(0.364)	(0.142)
Observations	1,625	1,625	1,625	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: The Effects of Immigration on Private Hospitals' Market Shares

The table shows regressions of the market shares of private (i.e., for-profit and nonprofit) hospitals in a county on instrumented immigration flows. Market shares are computed using hospital beds, numbers of hospitals, hospital admissions, outpatient visits, and Emergency Room (ER) visits. In column (1), control variables are the same as in Table 5, Panel A. Additional controls in column (2) are *log(GOV Hospitals)*, *log(NP Hospitals)*, *log(FP Hospitals)*, and *% Private Hospitals* in *t-10*. Additional controls in columns (3) to (5) are the logarithm of government, for-profit, and nonprofit admissions (column (3)), outpatient visits (column (4)), and ER visits (column (5)) in *t-10* and the percentage of private admissions (column (3)), outpatient visits (column (4)), and ER visits (column (5)) in *t-10*. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dep. Variables:	(1) ΔPrivate Beds Share (%)	(2) ΔPrivate Hosp Share (%)	(3) ΔPrivate Adm. Share (%)	(4) ΔPrivate Outp. Share (%)	(5) ΔPrivate ER Share (%)
Imm. Inflow (%)	-0.759**	-1.098***	-0.733***	-0.551	-0.876***
	(0.331)	(0.408)	(0.251)	(0.399)	(0.294)
Observations	1,625	1,625	1,625	1,621	1,619
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd

Table 8: Instrument Validity

The table presents reduced-form regressions to examine instrument balance. Dependent variables in columns (1) to (3) are county-level market shares of government, nonprofit, and for-profit hospitals based on hospital beds in year 2000. In columns (4) to (6), the dependent variables are the logarithm of the number of government, nonprofit, and for-profit hospital beds in year 2000. The key explanatory variable is the instrumental variable averaged across each county's five 10-year windows (2005-2015 to 2009-2019). Control variables include the counties' *log(Population)*, *log(Household Income)*, and *Poverty (%)* in 2000. Observations are weighted by the county's population. Variable definitions are in Appendix A. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dep. Variables:	Market Shares: Beds in 2000 (%)			Logs of Beds in 2000		
	(1)	(2)	(3)	(4)	(5)	(6)
	GOV	NP	FP	GOV	NP	FP
Mean Pred. Imm Inflow (%)	0.062	0.043	-0.105	-0.049	-0.019	-0.074*
	(0.430)	(0.539)	(0.394)	(0.073)	(0.032)	(0.043)
Observations	324	324	324	324	324	324
State FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
County controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	2000	2000	2000	2000	2000	2000

Table 9: The Effects of Immigration on Hospital Outcomes: Hospital-Level Analysis

The table presents regressions of hospital-level outcomes on instrumented immigration flows. The sample is a hospital-period panel and includes hospitals that did not change organizational form during the ten (or five)-year period. Panel A, column (1) shows the first-stage regression, and columns (2) and (3) show the second-stage regressions. Panel B is similar, but considers five-year (instead of ten-year windows, which allows us to examine changes in uncompensated care). The specification additionally controls for *t-5* uncompensated care in column (4). Panels C-E examine ten-year and five-year changes by organizational form. Variable definitions are in Appendix A. Regressions are unweighted. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Panel A: All hospitals over ten-year periods

Dep. Variables:	(1) Imm. Inflow (%)	(2) ΔMargin (%)	(3) ΔMedicaid (%)
Imm. Inflow (%)		-0.302**	0.056
		(0.154)	(0.247)
Pred. Imm. Inflow (%)	0.661***		
	(0.057)		
Log(Population)	-0.511**	-0.345	0.533
	(0.257)	(0.525)	(0.512)
Poverty (%)	17.159***	14.705	6.203
	(4.800)	(12.999)	(10.453)
Log(Household Inc.)	4.811***	7.061*	-1.518
	(1.571)	(3.654)	(3.338)
Top 50 Metro Area	0.948***	0.527	0.490
	(0.328)	(0.703)	(0.652)
Log(FP Beds)	0.021	-0.094	-0.033
	(0.061)	(0.125)	(0.103)
Log(NP Beds)	0.046	0.185	-0.112
	(0.078)	(0.221)	(0.155)
Log(GOV Beds)	-0.014	-0.250	-0.194
	(0.065)	(0.163)	(0.145)
% Private bed s	-0.982	0.638	-4.383**
	(0.806)	(2.220)	(1.944)
GOV Hospital	0.199**	-0.961	1.020
	(0.081)	(0.908)	(1.162)
FP Hospital	-0.028	3.180***	-1.383**
	(0.075)	(0.854)	(0.682)
Margin (%)	0.490**	-59.198***	0.173
	(0.230)	(3.133)	(1.619)
Medicaid (%)	0.003**	0.000	-0.419***
	(0.002)	(0.014)	(0.028)
Log(Beds)	-0.011	1.163***	1.882***
	(0.035)	(0.268)	(0.252)
System	0.077	1.189***	-0.441
	(0.081)	(0.426)	(0.421)
Observations	8,021	7,688	8,021
State-year FE	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes
Reg. Stage	1st	2nd	2nd
F test model	134		

Table 9: The Effects of Immigration on Hospital Outcomes: Hospital-Level Analysis, cont.

Panel B: All hospitals over five-year periods

Dep. Variables:	(1) Imm. Inflow (%)	(2) ΔMargin (%)	(3) ΔMedicaid (%)	(4) ΔUncomp. (%)
Imm. Inflow (%)		-0.411***	0.030	0.647***
		(0.152)	(0.284)	(0.177)
Pred. Imm. Inflow (%)	0.657***			
	(0.050)			
Observations	17,857	17,105	17,857	5,100
State-year FE	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes
Reg. Stage	1st	2nd	2nd	2nd
F test model	175.4			

Table 9: The Effects of Immigration on Hospital Outcomes: Hospital-Level Analysis, cont.

Windows:	Ten-Year			Five-Year		
	(1)	(2)	(3)	(4)	(5)	(6)

Panel C: Margins regressions by organization form

Dep. Variable:	ΔMargin (%)					
Sample:	GOV	NP	FP	GOV	NP	FP
Imm. Inflow (%)	-1.280*	-0.370**	0.545	-2.351**	-0.481**	0.292
	(0.654)	(0.187)	(0.344)	(1.056)	(0.222)	(0.452)
Observations	720	4,682	2,286	1,555	10,060	5,490
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd	2nd

Panel D: Medicaid regressions by organization form

Dep. Variable:	ΔMedicaid (%)					
Sample:	GOV	NP	FP	GOV	NP	FP
Imm. Inflow (%)	-0.905**	0.146	0.039	-0.493	0.096	-0.068
	(0.365)	(0.195)	(0.368)	(0.781)	(0.232)	(0.362)
Observations	770	4,845	2,406	1,666	10,416	5,775
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd	2nd

Panel E: Uncompensated care regressions by organization form

Dep. Variable:	ΔUncompensated (%)		
Sample:	GOV	NP	FP
Imm. Inflow (%)	2.027***	0.307**	0.351
	(0.593)	(0.140)	(0.242)
Observations	487	3,425	1,188
State-year FE	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd

Table 10: The Effects of Immigration on Nonprofit Hospital Investment and Financing

The table shows regressions of hospital investment and financing measures on instrumented immigration flows. In columns (1) to (5), the dependent variable is the change in the logarithm of hospital assets (or liabilities) from year *t-10* to *t*. In column (6), the dependent variable is the change in the hospital's leverage ratio from year *t-10* to *t*. Control variables include those in Table 9, Panel A. Additional control variables is the logarithm of total assets in *t-10* and the level of the respective dependent variable in *t-10* (for example, it is Log(*Fixed Assets*) in column (2) and *Leverage (%)* in column (6)). Variable Definitions are in Appendix A. Regressions are unweighted. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dep. Variables:	Changes in Logs of Hospital Assets (Liabilities) from *t-10* to *t*:					
	(1) Total Assets	(2) Fixed Assets	(3) Beds	(4) Fund Balances	(5) Liabilities	(6) ΔLeverage (%)
Imm. Inflow (%)	-0.605	-1.811**	0.414	-0.391	0.750	-0.062
	(0.918)	(0.890)	(0.835)	(1.946)	(1.443)	(0.547)
Observations	4,685	4,578	4,845	3,953	4,419	3,746
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd	2nd

Table 11: Nonprofit Hospital Investment and Financing by County Size

The table shows regressions of hospital investment and financing measures on instrumented immigration flows for samples split at the median of the county's total population in *t-10* for nonprofit hospitals in the sample. In columns (1) to (5), the dependent variable is the change in the logarithm of hospital assets (or liabilities) from year *t-10* to t. In columns (6) and (7), the dependent variable is the change in the hospital's leverage ratio or profit margin from year *t-10* to *t*. Control variables include those in Table 9, Panel A. Additional control variables is the logarithm of total assets in *t-10* and the level of the respective dependent variable in *t-10* (for example, it is Log(*Fixed Assets*) in column (2) and *Leverage (%)* in column (6)). Variable Definitions are in Appendix A. Regressions are unweighted. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dep. Variables:	Changes in Logs of Hospital Assets (Liabilities) from *t-10* to *t*:						
	(1) Total Assets	(2) Fixed Assets	(3) Beds	(4) Fund Balances	(5) Liabilities	(6) ΔLeverage (%)	(7) ΔMargin (%)
Panel A: Hospitals in high-population counties (above median)							
Imm. Inflow (%)	-7.536**	-5.455**	-1.662	-19.499***	2.873	2.887*	-1.673***
	(3.368)	(2.313)	(1.187)	(5.812)	(5.285)	(1.545)	(0.608)
Observations	2,342	2,275	2,409	1,885	2,188	1,778	2,339
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd	2nd	2nd
Panel B: Hospitals in low-population counties (below median)							
Imm. Inflow (%)	1.460	0.133	0.768	2.674	-0.580	-0.504	0.018
	(1.215)	(0.886)	(0.991)	(3.545)	(1.050)	(0.429)	(0.123)
Observations	2,343	2,303	2,436	2,068	2,231	1,968	2,343
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd	2nd	2nd

Table 12: The Effects of Immigration on Hospital Acquisitions and Closures

The table shows regressions of indicators for hospital acquisitions and closures on instrumented immigration flows. In Panel A, the dependent variable is equal to one if the hospital is acquired by a system during t-10 to t. The panel consists of 1,612 hospitals and five ten-year periods from 2005-2015 to 2009-2019 (5,908 hospital-period observations). We consider separately acquisitions by for-profit or nonprofit systems, only nonprofit systems, and only for-profit systems. Hospitals with multiple acquisitions during a period are classified based on the organizational form of the first acquirer. The average ten-year system acquisition frequencies are 24% for for-profit and nonprofit acquirers, 17% for nonprofit acquirers, and 8% for for-profit acquirers. In Panel B, the dependent variable is an indicator for hospital closure during the ten-year period. The sample is no longer restricted to hospitals that survive the ten-year period. The average frequency of closures during the ten-year period is 2%. The control variables in both panels is the same as in Table 9, Panel A. Variable Definitions are in Appendix A. Regressions are unweighted. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Panel A: The effects of immigration on the likelihood of hospital acquisitions by systems: split by organizational forms of systems and target hospitals

Dep. Variables:	Imm. Inflow (%)	Acquisition by FP or NP System>0			Acquisition by NP System>0			Acquisition by FP System>0		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hospital sample:	FP & NP	FP & NP	NP	FP	FP & NP	NP	FP	FP & NP	NP	FP
Imm. inflow 10-y (%)		0.010*	0.014*	-0.011	-0.006	-0.008	-0.005	0.017***	0.023***	-0.009
		(0.006)	(0.008)	(0.011)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.010)
Pred. Imm. Inflow (%)	0.693***									
	(0.058)									
Observations	5,908	5,908	3,980	1,928	5,908	3,980	1,928	5,908	3,980	1,928
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	1st	2nd	2nd	2nd	2nd	2nd	2nd	2nd	2nd	2nd
F test model	141.4									

Table 12: The Effects of Immigration on Hospital Acquisitions and Closures, cont.

Panel B: The effects of immigration on the likelihood of hospital closure: by hospital organization form

Dep. Variable:	Hospital Closure > 0		
	(1)	(2)	(3)
Sample:	FP & NP	NP	FP
Imm. Inflow (%)	0.007***	0.006**	0.007**
	(0.002)	(0.002)	(0.004)
Observations	6,895	4,511	2,384
State-year FE	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd

Internet Appendix Figures

Figure A1: Percentage of Foreign-Born Residents Living in the U.S.

The figure shows the fraction of foreign-born nationals living in the U.S. in proportion to the overall population based on U.S. Census IPUMS data from 2005-2019.

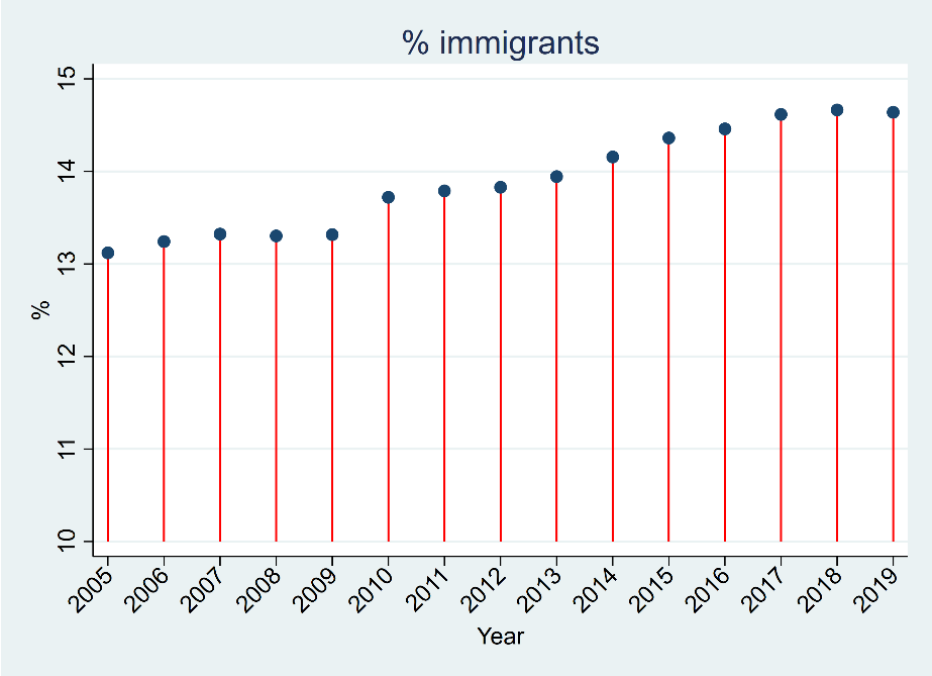


Figure A2: Top Seven Countries of Origin for U.S. Foreign-Born Residents in 2000

The figure shows the top seven countries of origin for foreign-born residents in the U.S. according to the 2000 U.S. Census. It presents each country's share of the total foreign-born population in the U.S.

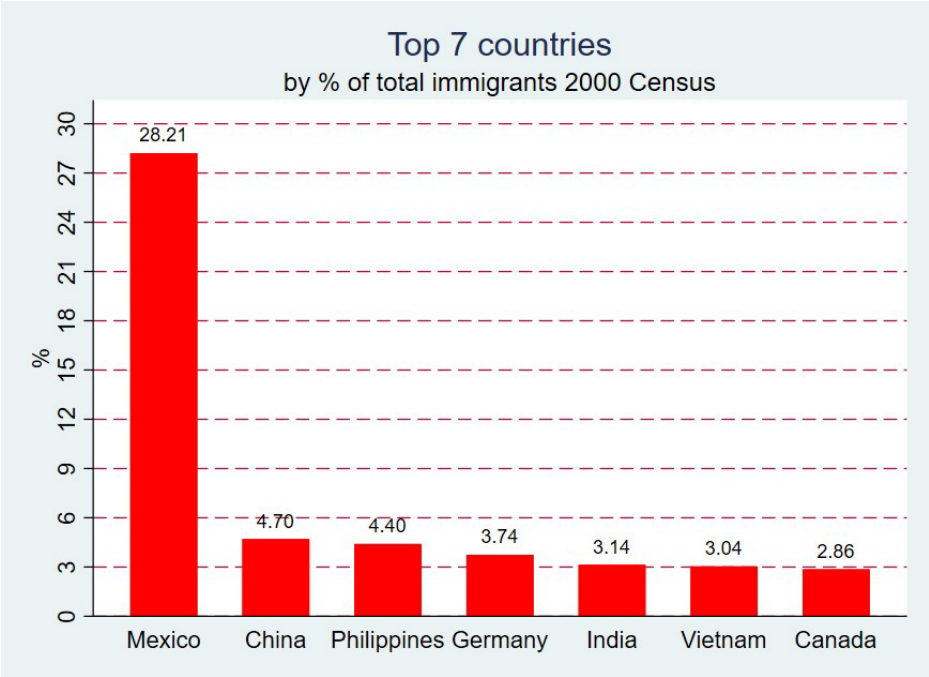


Figure A3: Top Seven Countries of Origin for Immigration Inflows by Time Period

The figure shows the top seven countries of origin for foreign-born nationals immigrating to the U.S. for each of the four five-year periods from 2000 to 2019. For each country of origin and period, the figures show the fraction of immigrants from that country in percent of all immigrants entering the U.S. during that period.

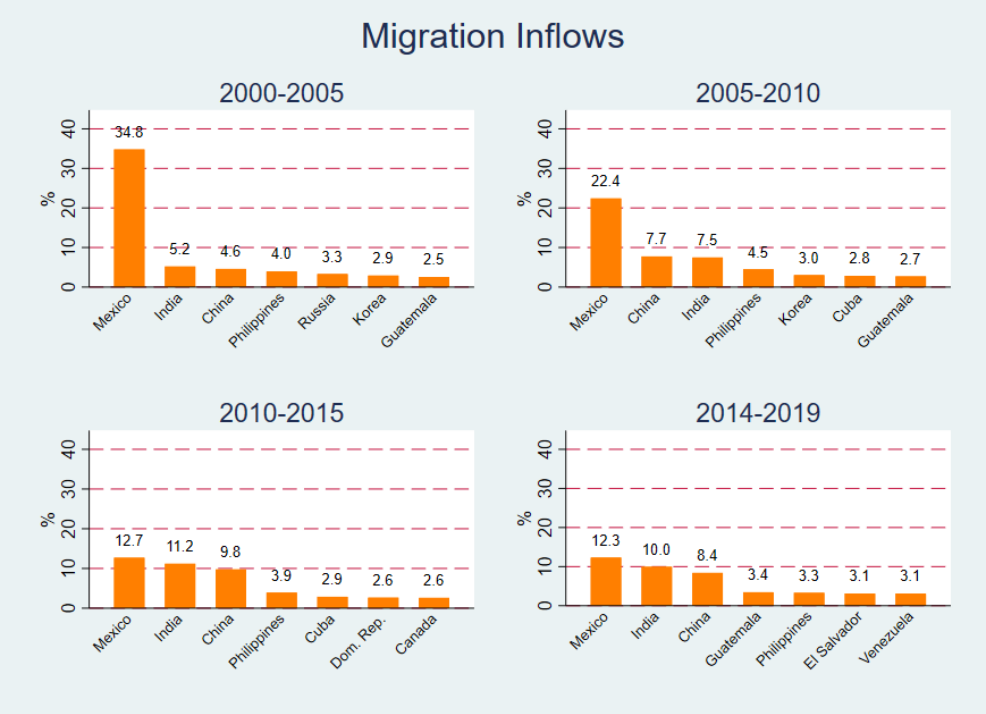


Figure A4: Top Seven Countries of Origin by Migration Inflows Averaged Over Five Ten-Year Periods

The figure shows the top seven countries of origin for U.S. immigrants from 2005 to 2019. For each country and period (2005-2015, 2006-2016, 2007-2017, 2008-2018, and 2009-2019), we compute the fraction of immigrants from that country in percent of all immigrants entering the U.S. during that period. The figure shows averages of the fractions across all five ten-year periods.

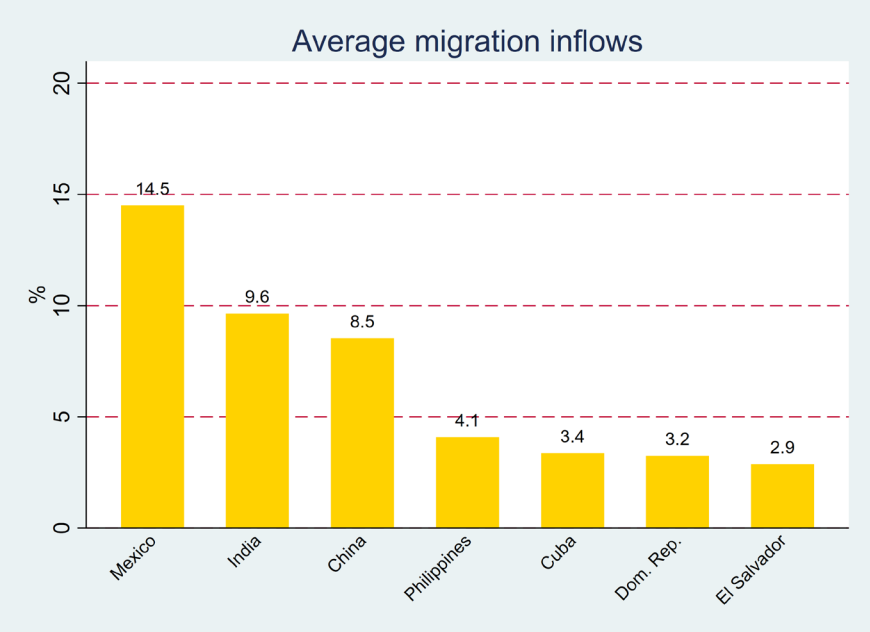


Figure A5: Distribution of County-Year Observations by U.S. State

The figure shows the number of observations by state corresponding to the 1,625 county-year observations in the main sample.

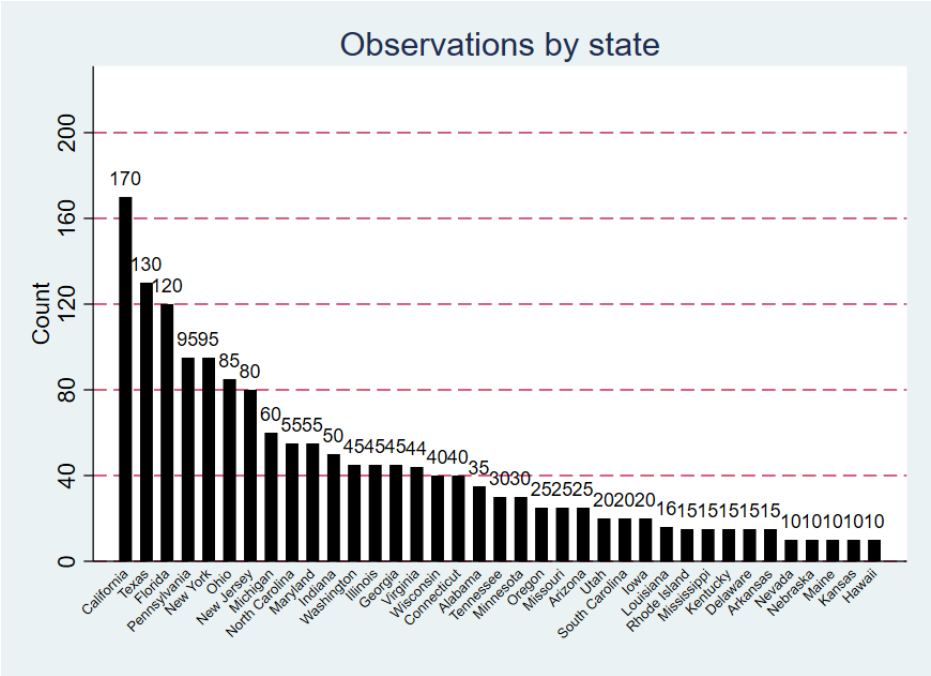


Figure A6: Distribution of Counties by Type.

The figure shows the number of observations by county-type corresponding to the 1,625 county-year observations in the main sample.

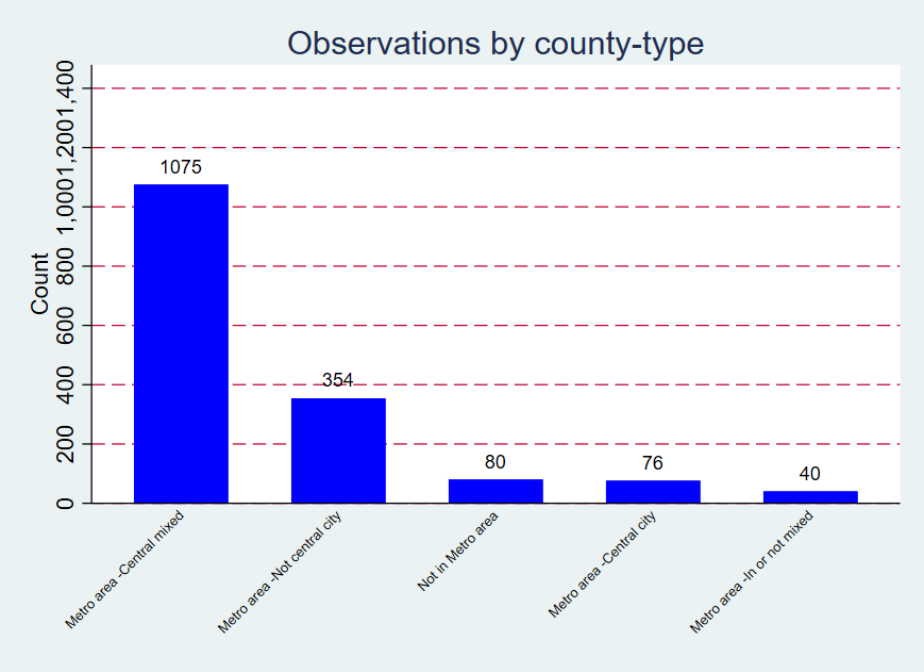
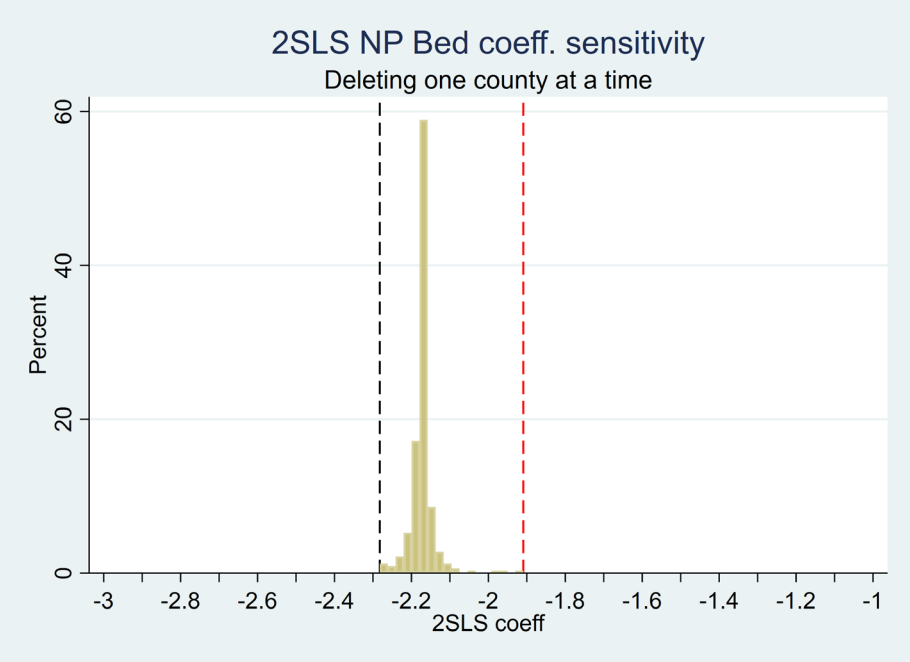


Figure A7: Estimates Excluding One County at a Time

Panel A shows the distribution of the IV coefficients for *Imm. Inflow (%)* obtained when estimating the effects on Δ*NP Beds / Beds (%)* (Table 5, Panel A, column 3) on sub-samples where we exclude one county at a time. Panel B shows the distribution of p-values for the *Imm. inflow (%)* coefficients. Dashed vertical lines mark the minimum and maximum in each panel.

Panel A: Coefficient estimates when removing one county at a time



Panel B: P-values obtained when removing one county at a time

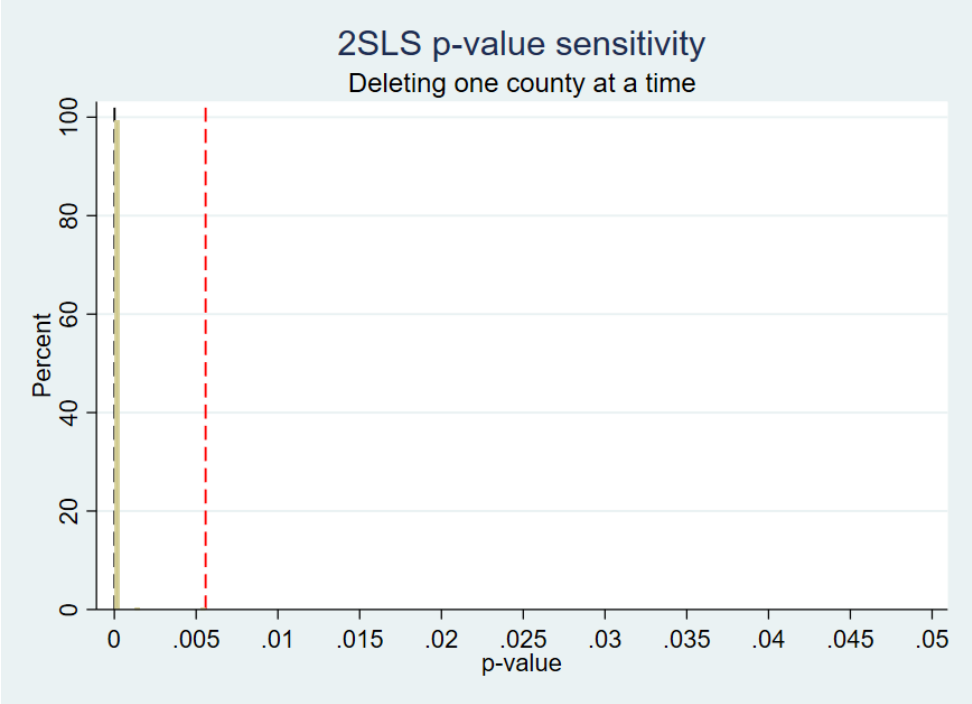
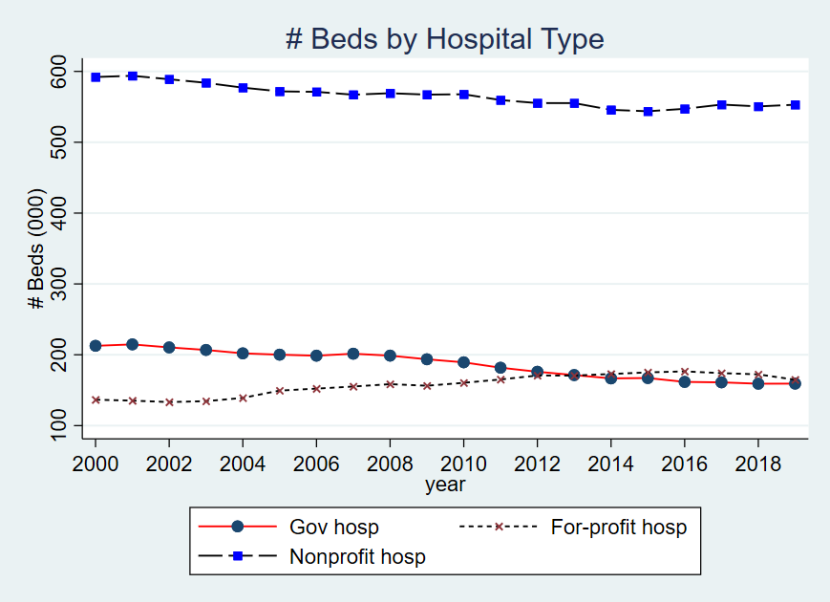


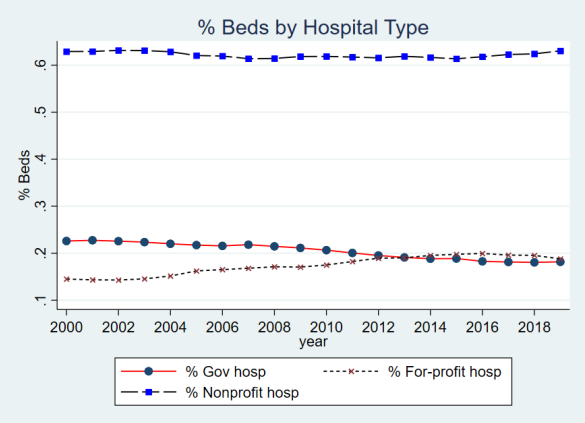
Figure A8: Hospital Beds over Time by Organizational Form after Excluding Federal Hospitals

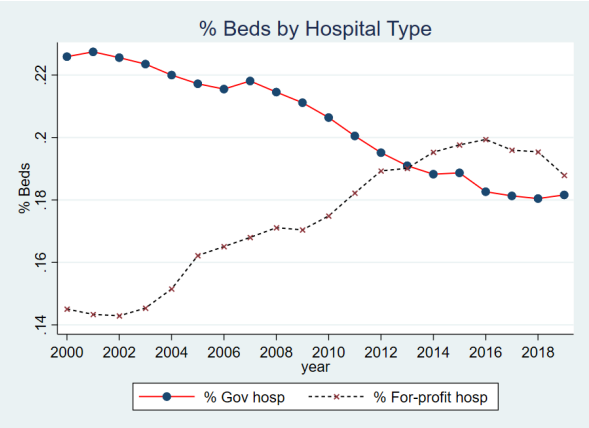
Panel A shows the total number of hospital beds by hospitals' organizational form reported in the AHA's Annual Survey Database from 2000 to 2019 (in thousands), excluding hospitals affiliated with military or veterans' hospital systems. Panel B shows market shares based on hospital beds of nonprofit, for-profit, and government hospitals by year (in percent). The right figure focuses on market shares of for-profit and government hospitals.

Panel A: Number of beds (in thousands) over time by organizational form



Panel B: Fraction of beds (in percent) over time by organizational form





Internet Appendix Tables

Table A1: The Effects of Immigration on County-Level Income and Poverty

The table shows regressions of the county-level demographic outcomes on instrumented immigration flows. *Δ Household Income (%)* is the change in the county's median household income from *t-10* to *t* scaled by the median income in *t-10*. *ΔPoverty Rate (%)* is the change in the county's poverty rate from *t-10* to *t*. Control variables include *log(Population)*, *log(Household Income)*, *Poverty (%)*, *Top 50 Metro Area*, *log(FP Beds)*, *log(NP Beds)*, *log(GOV Beds)*, and *% Private Beds* in the county in *t-10*. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

	(1)	(2)
Dependent Var.:	ΔHousehold Income (%)	ΔPoverty Rate (%)
Imm. Inflow (%)	1.483**	-0.132**
	(0.663)	(0.052)
Observations	1,625	1,625
State-year FE	Yes	Yes
County-type FE	Yes	Yes
Controls	Yes	Yes
Reg. Stage	2nd	2nd

Table A2: The Effects of Immigration on Hospital Admissions: County-Level Analysis

The table shows regressions of the county-level hospital outcomes on instrumented immigration flows. The dependent variables are changes from *t-10* to *t* in hospital admissions in a county categorized by the hospital's organizational form, with all changes being scaled by the total admissions in the county in *t-10*. Control variables include those in Table 5, Panel A and also include *log(GOV Admissions)*, *log(NP Admissions)*, *log(FP Admissions)*, and *% Private Admissions* in *t-10*. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

	(1)	(2)	(3)	(4)	(5)
Dep. Variables:	ΔAdm. / Adm. (%)	ΔGOV Adm. / Adm. (%)	ΔNP Adm. / Adm. (%)	ΔFP Adm. / Adm. (%)	ΔPriv. Adm. / Adm. (%)
Imm. Inflow (%)	-2.533***	0.153	-2.694***	0.009	-2.685***
	(0.503)	(0.267)	(0.431)	(0.376)	(0.536)
Observations	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd

Table A3: Robustness Tests: Excluding Large Migrant Groups

The table shows the first-stage and second-stage regression results, analogous to those in Table 4, column (1) and Table 5, Panel A, column (3), but excluding the three largest groups of immigrants from the numerators of the predicted and actual immigration inflows. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Excluded Groups:	Mexicans		Chinese		Indians	
Dep. Variables:	Imm. Inflow (%)	ΔNP Beds / Beds (%)	Imm. Inflow (%)	ΔNP Beds / Beds (%)	Imm. Inflow (%)	ΔNP Beds / Beds (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Imm. Inflow (%)		-1.754***		-2.326***		-2.645***
		(0.465)		(0.604)		(0.703)
Pred. Imm. Inflow (%)	0.706***		0.681***		0.630***	
	(0.039)		(0.043)		(0.063)	
Observations	1,625	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	1st	2nd	1st	2nd	1st	2nd
F test model	332.8		252.9		100.4	

Table A4: Robustness Tests: Unweighted Regressions, Alternative Base Year, and Treatment of Foreign-Born Domestic Migrants

The table shows the first-stage and second-stage regression results, analogous to those in Table 4, column (1) and Table 5, Panel A, column (3) with the following modifications: in the left panel, county-level observations are equal weighted (rather than weighted by the county's population in *t-1*); in the middle panel, year 1990 (rather than 2000) is used as the historical (base) Census year to construct enclaves (i.e., the initial distribution of immigrants across counties, $S_{c,f,h}$); in the right panel, we study immigration *net flows* into a county *c* during *t-10* to *t.* This includes recent immigrants relocating to the US, as well as foreign-born people that have been living in the U.S. prior to migrating into the county during *t-10* and *t* and substracts foreign-born people that moved out of the county between *t-10* and *t*. In the main analysis, only recent immigrants – those that moved to the US in the last ten years – are included. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Weighting:	Equal Weighted		Population Weighted		Population Weighted	
Base Year:	2000		1990		2000	
Immigration Flow	Recent Inflows		Recent Inflows		Net Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variables:	Imm. Inflow (%)	ΔNP Beds / Beds (%)	Imm. Inflow (%)	ΔNP Beds / Beds (%)	Migration. Net Flow (%)	ΔNP Beds / Beds (%)
Imm. Inflow (%)		-1.339**		-3.287***		-3.344***
		(0.651)		(1.057)		(1.208)
Pred. Imm. Inflow (%)	0.750***		0.404***		0.380***	
	(0.044)		(0.107)		(0.074)	
Observations	1,625	1,625	1,326	1,326	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	1st	2nd	1st	2nd	1st	2nd
F test model	293.1		14.32		26.17	

Table A5: Robustness Tests: Individual Ten-Year Windows

The table shows regression results, analogous to those in Table 5, Panel A, column 3, but estimating the regressions separately for each ten-year window. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dep. Variable:	ΔNP Beds / Beds (%)				
Sample:	2005-2015	2006-2016	2007-2017	2008-2018	2009-2019
	(1)	(2)	(3)	(4)	(5)
Imm. Inflow (%)	-2.501***	-2.393***	-2.033***	-1.647**	-2.322***
	(0.613)	(0.603)	(0.656)	(0.796)	(0.725)
Observations	325	325	325	325	325
State FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd

Table A6: Robustness Tests: Five-Year Windows

The table shows regression results, analogous to those in Table 5, Panel A, but using ten five-year windows from 2005-2010 to 2014-2019 instead of five ten-year windows. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dep. Variables:	(1) ΔBeds / Beds (%)	(2) ΔGOV Beds / Beds (%)	(3) ΔNP Beds / Beds (%)	(4) ΔFP Beds / Beds (%)	(5) ΔPrivate Beds / Beds (%)
Imm. Inflow (%)	-2.418**	0.257	-2.339***	-0.336	-2.675***
	(0.962)	(0.389)	(0.513)	(0.563)	(0.891)
Observations	3,340	3,340	3,340	3,340	3,340
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd

Table A7: Robustness Tests: MSA-level Analysis

The table shows regression results, analogous to those in Table 5, Panel A, but using five ten-year windows from 2005-2010 to 2014-2019 at the MSA level instead of the county level. Hospital data is aggregated at the MSA level using the 2005 county-MSA link. There are 215 MSAs for which we can identify foreign-born residents during the study period. The average MSA in our sample has a population of 934,000, with 10% of residents being foreign-born. The F-test of the first-stage regression is 250. Control variables include *Top 50 Metro Area*, *log(FP Beds)*, *log(NP Beds)*, *log(GOV Beds)*, and *% Private Beds* in the MSA in *t-10*. Variable definitions are in Appendix A. Observations are weighted by the MSA's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dep. Variables:	(1) ΔBeds / Beds (%)	(2) ΔGOV Beds / Beds (%)	(3) ΔNP Beds / Beds (%)	(4) ΔFP Beds / Beds (%)	(5) ΔPrivate Beds / Beds (%)
Imm. Inflow (%)	-1.813***	0.147	-1.321***	-0.639**	-1.961***
	(0.682)	(0.481)	(0.508)	(0.324)	(0.643)
Observations	1,075	1,075	1,075	1,075	1,075
State-year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd

Table A8: Robustness Tests: Excluding Veterans' and Military Hospitals

The table shows results for the main county-level analysis after excluding veterans' and military-affiliated hospitals from the sample. Panel A shows county-level variables measured at the beginning of the ten-year periods (*t-10*), similar to Table 2, Panel A. Panel B shows the second-stage regressions analogous to those in Table 5, Panel A. Variable definitions are in Appendix A. Observations are weighted by the county's population in *t-10*. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Panel A: Descriptive statistics for levels as of beginning of the measurement period

	Mean	P10	P50	P90	SD	N
Beds	1,534.12	216.00	720.00	3,727.00	2,361.87	1,625
GOV Beds	272.11	0.00	16.00	776.00	537.00	1,625
NP Beds	997.88	48.00	448.00	2,431.00	1,586.50	1,625
FP Beds	264.14	0.00	46.00	637.00	650.03	1,625
Hospitals	7.02	2.00	4.00	15.00	9.80	1,625
GOV Hospitals	0.97	0.00	1.00	3.00	1.52	1,625
NP Hospitals	3.83	1.00	2.00	8.00	5.31	1,625
FP Hospitals	2.22	0.00	1.00	5.00	4.69	1,625
% GOV Beds	16.12	0.00	0.92	52.69	24.09	1,625
% NP Beds	67.63	9.67	75.13	100.00	32.11	1,625
% FP Beds	16.26	0.00	4.33	49.56	24.51	1,625
Admissions (000)	66.31	10.44	30.02	166.21	103.71	1,625
Outpatient Visits (000)	997.79	158.30	506.75	2,302.82	1,459.49	1,625
ER Visits (000)	196.84	42.49	101.67	442.89	266.22	1,625
% Private Hospitals	85.37	50.00	96.00	100.00	21.24	1,625
% Private Admissions	88.24	61.33	99.89	100.00	23.18	1,625
% Private Outpatient Visits	85.63	44.11	100.00	100.00	25.91	1,625
% Private ER Visits	87.64	55.83	100.00	100.00	24.50	1,621

Panel B: Regressions of changes in the number of beds in percent of total beds in t-10

Dep. Variables:	(1) ΔBeds / Beds (%)	(2) ΔGOV Beds / Beds (%)	(3) ΔNP Beds / Beds (%)	(4) ΔFP Beds / Beds (%)	(5) ΔPrivate Beds / Beds (%)
Imm. Inflow (%)	-2.115**	0.253	-2.165***	-0.204	-2.368**
	(1.031)	(0.384)	(0.550)	(0.537)	(0.929)
Observations	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd

Table A9: Robustness Tests: Alternative Instrument

The table presents first-stage and second-stage regressions using Burchardi et al.'s (2019, 2024) instrument for predicted immigration. They exploit historical migration patterns to instrument for the enclaves (instead of constructing enclaves based on the actual historical distribution of the ethnic groups across the U.S.). Burchardi et al. (2024) study five-year immigration flows from 1980-2010 and do not scale immigration flows by the counties' populations to construct actual or instrument flows (that is, they use immigration flows in thousands of people). To match their specification, in this table, we also use five-year windows. Panel A shows results from first-stage regressions using both unscaled immigration flows in columns (1) and (2) and immigration flows scaled by the county's population in *t-5* in columns (3) to (5). *IIG Instrument (000)* is Burchardi et al.'s (2024) instrument for the number of recent immigrants in thousands, with *IIG* standing for the title of their 2024 paper "Immigration, Innovation, and Growth." *IIG Instrument (%)* is their instrument scaled by the county's population in *t-5*. The regression in column (1) uses the instrument provided by Burchardi et al. (2024) (available on their website) and uses their sample period but includes only counties we can identify in our sample. Column (2) presents similar results but restricts the sample to the one five-year window that overlaps with our data: 2005-2010 (we do not use this window in the main analysis as it is too close to our historical Census year of 2000). In columns (3) to (5), we scale both the actual and the instrumented flows by the counties' population in *t-5*, consistent with the specification in this paper and in other literature. In column (4), we control for county-type fixed effects, and in column (5), we add the full set of controls used in our main analysis (Table 5, Panel A). In columns (2) to (4), observations are equally weighted and in column (5), they are weighted by the county's population in *t-5*. In Panel B, we present regressions similar to Burchardi et al. (2024), Equation (1), using Burchardi et al.'s instrument (unscaled) alongside our immigration inflows (unscaled) for the only overlapping measurement window of 2005-2010. In Panel C, we repeat these tests using the standard enclave instrument (but in levels) for comparison. Variable definitions are in Appendix A. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Panel A: First-stage regressions using the IIG instrument and unscaled or scaled immigration flows

Dep. Variables:	(1) Imm. Inflow (000)	(2) Imm. Inflow (000)	(3) Imm. Inflow (%)	(4) Imm. Inflow (%)	(5) Imm. Inflow (%)
IIG Instrument (000)	3.383***	3.206***			
	(0.495)	(0.381)			
IIG Instrument (%)			0.997**	0.230	0.027
			(0.382)	(0.263)	(0.280)
Observations	3,140	368	368	368	368
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	No	No	No	Yes	Yes
Controls	No	No	No	Yes	Yes
Sample	1980-2010	2005-2010	2005-2010	2005-2010	2005-2010
Weight	EW	EW	EW	EW	Population
F test model	46.66	70.65	6.828	0.766	0.00967

Table A9: Robustness Tests: Alternative Instrument, cont.

Dep. Variables:	(1) Imm. Inflow (000)	(2) ΔBeds	(3) ΔGOV Beds	(4) ΔNP Beds	ΔFP Beds	(5) ΔPrivate Beds
Panel B: Estimating the effects of immigration using the IIG instrument unscaled						
Imm. Inflow (000)		-1.373***	0.794**	-1.230***	-0.937*	-2.167***
		(0.475)	(0.386)	(0.403)	(0.490)	(0.558)
IIG Instrument (000)	4.582***					
	(0.281)					
Observations	368	368	368	368	368	368
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	No	No	No	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Sample	2005-2010	2005-2010	2005-2010	2005-2010	2005-2010	2005-2010
Weight	EW	EW	EW	EW	EW	EW
Reg. Stage	1st	2nd	2nd	2nd	2nd	2nd
F test model	266.6					
Panel C: Estimating the effects of immigration using the standard enclave instrument unscaled						
Imm. Inflow (000)		-2.705**	0.729	-2.386**	-1.048**	-3.434***
		(1.067)	(0.452)	(1.102)	(0.436)	(0.932)
Pred. Imm. Inflow (000)	0.583***					
	(0.051)					
Observations	368	368	368	368	368	368
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	No	No	No	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Sample	2005-2010	2005-2010	2005-2010	2005-2010	2005-2010	2005-2010
Weight	EW	EW	EW	EW	EW	EW
Reg. Stage	1st	2nd	2nd	2nd	2nd	2nd
F test model	131.5					

Table A10: The Effects of Immigration on Nonprofit Hospital Donations and Contributions

The table shows regressions of hospital donations and government contributions on instrumented immigration flows. The dependent variables are the change from *t-10* to *t* in the ratio of hospital private donations (or total contributions, including private donations plus government grants) to revenues. Control variables include those in Table 9, Panel A. Additional control variables are the logarithm of total assets in *t-10* and the level of the respective dependent variable in *t-10* (for example, it is *Donation (%)* in column (1)). Variable definitions are in Appendix A. Regressions are unweighted. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

	(1)	(2)
Dep. Variables:	ΔDonation (%)	ΔContribution (%)
Imm. Inflow (%)	-0.021	0.023
	(0.034)	(0.044)
Observations	1,402	1,271
State-year FE	Yes	Yes
County-type FE	Yes	Yes
Sample	NP Hosp	NP Hosp (IRS 990)
Reg. Stage	2nd	2nd

Table A11: Nonprofit Hospital Investment and Financing by Hospital Size and System Affiliation

The table shows regressions of hospital investment and financing measures on instrumented immigration flows, analogous to those in Table 11. In Panel A, hospitals are split based on whether they are affiliated with a system; in Panel B, they are split based on their *t-10* total assets. Variable definitions are in Appendix A. Regressions are unweighted. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Dep. Variables:	Changes in Logs of Hospital Assets (Liabilities) from *t-10* to *t*:						
	(1) Total Assets	(2) Fixed Assets	(3) Beds	(4) Fund Balances	(5) Liabilities	(6) ΔLeverage (%)	(7) ΔMargin (%)
Panel A: Hospitals split based on system affiliation							
			Affiliated Hospitals				
Imm. Inflow (%)	-0.329	-1.041	-0.276	0.793	-0.180	-0.403	-0.519*
	(1.307)	(1.604)	(1.097)	(2.412)	(2.170)	(0.567)	(0.265)
Observations	2,796	2,723	2,908	2,322	2,565	2,143	2,796
			Unaffiliated Hospitals				
Imm. Inflow (%)	0.199	-0.770	1.337	-3.517	2.895**	0.625	-0.130
	(1.101)	(1.717)	(0.920)	(4.583)	(1.473)	(0.742)	(0.171)
Observations	1,889	1,855	1,937	1,631	1,854	1,603	1,886
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd	2nd	2nd
Panel B: Hospitals split based on size							
			Large Hospitals				
Imm. Inflow (%)	-1.718	-2.214	-0.318	-1.938	-0.645	0.043	-0.512**
	(1.156)	(1.672)	(0.788)	(2.140)	(1.681)	(0.578)	(0.213)
Observations	2,372	2,316	2,424	2,203	2,257	2,114	2,371
			Small Hospitals				
Imm. Inflow (%)	0.069	-1.151	1.152	-0.571	2.546	-0.513	-0.305
	(1.299)	(2.332)	(0.917)	(4.236)	(2.480)	(0.638)	(0.245)
Observations	2,313	2,262	2,421	1,750	2,162	1,632	2,311
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2nd	2nd	2nd	2nd	2nd	2nd	2nd

Table A12: Descriptive Statistics for Hospital-Years Split Based on County's Population

The table presents a comparison of subsamples of the hospital-years used in Table 3 (or Table 9, Panel A) split based on whether the hospital-year is above or below the sample median of the county's population in t-10 *HHI* (both at the county and Hospital Service Area (HSA) level) is the Herfindahl–Hirschman index computed using market shares based on hospital beds, where beds are aggregated at the system level if a hospital is part of a system. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Variable	Small Counties	Large Counties	Diff.
Population (000)	344.32	2,704.43	2,360.10***
Household Income ($000)	50.89	54.78	3.89***
Poverty (%)	13.11	13.36	0.24
Top 50 Metro Area	0.39	1.00	0.61***
Uninsured % (<138% FPL)	29.20	31.80	2.60*
Beds	1,391.03	8,228.67	6,837.64***
Hospitals	6.73	34.83	28.10***
% GOV Beds	0.17	0.20	0.03
% NP Beds	0.64	0.61	-0.03
% FP Beds	0.19	0.19	-0.00
County HHI	0.39	0.15	-0.24***
HSA HHI	0.56	0.41	-0.15***
Margin	0.05	0.04	-0.01**
N	4,028	3,993	