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

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Abstract

We examine corporate responses of U.S. hospitals to local immigration inflows, focusing on nonprofits. Using historical enclaves of foreign-born nationalities to instrument for immigration inflows, we find that a 1% increase in immigration (relative to a county's initial population) leads to a 2.16% decline in hospital bed capacity over ten years. This contraction is driven primarily by nonprofit hospitals, which are more likely to exit through closures or mergers. Continuing nonprofits experience significant declines in profit margins and increases in uncompensated care; they respond by reducing capital investments rather than raising external funds. The evidence points to high uninsurance rates among recent immigrants as a key channel. More generally, the results suggest that nonprofit hospitals face tight financing and operating constraints that limit their ability to absorb profitability shocks and sustain mission-driven objectives. Government-owned hospitals experience comparably large losses but avoid exit and expand market shares, while for-profit hospitals limit exposure to unprofitable operations and acquire nonprofit assets.

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1. Introduction

Immigrants have accounted for over half of U.S. population growth since 1965, and the foreign-born share of the U.S. population reached 15.8% in 2025 (The Pew Research Center, 2015; 2025). The geographic distribution of foreign-born individuals within the United States is uneven, with inflows often concentrated in specific geographic areas. This paper examines the effects of immigration inflows on the U.S. hospital sector. Because immigrants have significantly lower rates of health insurance coverage, these flows can create large and persistent shocks to the local healthcare systems. From a corporate finance standpoint, these shocks provide a valuable setting for studying the behavior and constraints of U.S. hospitals. We focus on nonprofits, which dominate the sector, but whose decision-making remains poorly understood. At the same time, understanding how hospitals respond to immigration-induced demographic shifts is directly relevant for public policy.

The key challenge in estimating the effects of immigration is that immigrant flows are endogenous to the local economic conditions of the receiving country. To address this challenge, we exploit the tendency of newly arriving immigrants to settle in their own nationalities' historical enclaves (Card 2001, 2009). Identification comes from interacting the historical geographic distribution of these enclaves across the United States with national-level immigration inflows. As we explain in Section 4, the hospital context is especially well suited for the application of this canonical enclave instrument. Moreover, our estimates prove robust across a wide range of specifications and sensitivity analyses.[1]

This empirical strategy yields a stark and consistent set of results. As immigration inflows rise, the share of uninsured residents increases. Local hospital sectors contract in response, driven by nonprofit exits—both closures and mergers. Surviving nonprofits experience persistent declines in profit margins, accompanied by growth in uncompensated care. These losses are not offset by donations, debt issuance, or cross-subsidization; instead, affected nonprofits cut investment while public hospitals expand market shares. These findings underscore the vulnerability of the nonprofit sector when faced with rising demand for uncompensated care. They also highlight the role of

[1] The results are robust to 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.

public hospitals as de facto insurers of last resort. More broadly, the results illustrate how such demand shocks reorganize local healthcare markets, shifting activity from private nonprofits to publicly funded providers.

Our main interest lies in understanding hospitals' responses to an immigration shock, focusing on nonprofits as the dominant organizational form. Distinguishing among the theoretical models of nonprofit behavior—which range from serving donors or taxpayers to pursuing insider objectives or operating like profit-maximizing firms—has proven difficult, as real-world behavior often spans multiple frameworks. Our approach is to impose minimal structure, starting from basic accounting identities that every nonprofit must satisfy in each period. This framework allows us to track and bound the set of feasible responses to any economic shock. A hospital experiencing a persistent loss in one part of its operations must necessarily: (i) increase profits elsewhere, (ii) raise donations or grants, (iii) expand liabilities, or (iv) cut investment. Failing these options, it must eventually exit through merger or closure. We use these identities to organize our empirical analysis, first examining the sector as a whole at the county level and then decomposing responses by organizational form.

We begin the empirical analysis by establishing basic facts about how immigration flows affect local populations, providing context for our main results. As expected, we find that immigration significantly increases the share of uninsured residents among low-income populations. We also detect a negative, though insignificant, effect on the native population growth.[2] These patterns point to two channels through which immigration may affect local hospitals: (i) an "uninsurance channel," operating through a higher share of uninsured patients; and (ii) a "demand channel," operating through changes in the overall demand for healthcare services—for instance, if recent immigrants are healthier or initially consume less care, as suggested by prior work (summarized in Section 2). While both channels may be at work, we provide direct causal evidence supporting the uninsurance channel as a key mechanism.

The first striking finding is that immigration flows lead to a contraction of local hospital markets, caused entirely by hospital exits. An instrumented 1% increase in immigration over a decade (relative to the initial population) reduces total hospital beds by 2.16% and the number of

[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)).

hospitals by 2.10%. These estimates imply that a one-standard-deviation increase in immigration inflow into a county leads to an approximately 6.0% decline in both beds and hospitals over ten years—despite no long-term decline in county population. As the average county in our sample has 7.25 hospitals, this decline corresponds to the exit of 0.4 hospitals over ten years.[3] These magnitudes are consistent with many hospitals operating close to their financial break-even points. Decomposing the effects reveals that the contraction is driven by nonprofit hospitals. For-profit hospitals exhibit small and statistically insignificant declines, while public hospitals—directly funded by government budgets—expand their market shares (relative to areas unaffected by immigration flows). The net effect is a shift in ownership from private (especially nonprofit) to public hospitals. This shift offsets the long-run secular decline in public hospital ownership during our sample period (Online Appendix Figure A.1).

To shed light on the mechanisms, we turn to hospital-level financial data. Hospital profit margins incorporate both uncompensated care expenditures (e.g., discounts for uninsured patients or bad-debt write-offs) and revenues from donations or grants. If hospitals were offsetting losses from uncompensated care by earning higher margins elsewhere or by attracting more contributions, margins would be unaffected. Instead, we find that immigration causes substantial declines in hospital profit margins accompanied by increases in uncompensated care. For nonprofits, a 1% increase in immigration over ten years reduces margins by 0.37%, relative to an average margin of 3.66%. These magnitudes represent large but economically plausible reductions in revenues induced by the demographic shift. The effects are stronger for publicly funded hospitals that take on more charity care, and in more populous counties, where the financial pressures may have been more intense.

The failure to make up the immigration-induced financial shortfalls by increased profits or contributions implies that hospitals must either borrow more or invest less. We find evidence of the latter effect, with the impact again most pronounced in the populous counties: in these areas, a 1% increase in immigration reduces nonprofit hospitals' fixed assets by 5.5% and correspondingly lowers their fund balances (analogous to equity). Although hospitals raise no new debt, their leverage rises mechanically. These patterns are consistent with the elevated rates of closures and

[3] Because we rely on immigration data provided by the U.S. Census, our analysis focuses on large counties, which together account for more than 50% of the U.S. population (see details in Section 5.2).

mergers discussed earlier, which likely reflect prolonged financial distress. They also underscore the strong link between nonprofits' ability to generate profits and their capacity to pursue mission-driven objectives.

The paper contributes to three distinct strands of literature. First, it adds to the growing healthcare finance literature examining hospital investment, private equity, and nonprofit governance (Adelino, Lewellen, and Sundaram 2015; Adelino, Lewellen, and McCartney 2022; Aghamolla et al. 2024; Gupta, Howell, and Yannelis 2024; Gao, Lee, and Murphy 2022; Gao, Kim, and Sevilir 2024; Cornaggia, Li, and Ye 2024; Lewellen, Phillips, and Sertsios 2025; Gao, Li, Malik, and Sevilir 2026). Our contribution is to analyze a large, localized shock that induces persistent financing shortfalls and to trace nonprofit hospitals' subsequent adjustments across their operations, investment, financing, and survival. By using basic accounting identities to track feasible responses, our approach imposes minimal structure, providing a comprehensive view of nonprofit corporate financial behavior under stress.

Second, we contribute to the extensive literature on the effects of immigration on the U.S. economy, including labor markets, public finances, housing, productivity, and innovation (Lewis and Peri 2015; Dustmann, Schönberg, and Stuhler 2016). While recent finance work examines immigration's impact on local government finances (Cornaggia, Cornaggia, and Israelsen 2025; Zimmerschied 2025), there is a significant gap regarding the healthcare sector. Existing studies (reviewed in Section 2) focus primarily on immigrants' health outcomes, healthcare utilization, and insurance coverage. To our knowledge, this is the first comprehensive analysis to link immigration shocks to both hospital-level financial behavior and the resulting structural reorganization of local healthcare systems.

Finally, the paper contributes to the literature on hospital organizational form in health economics (Sloan 2000; Gaynor, Ho, and Town 2015). Much of this work focuses on efficiency, market structure, or clinical decisions rather than corporate finance.[4] The closest related strand is

[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)).

the literature on "cost shifting," which examines whether hospitals raise prices to private insurers to offset public program losses. Our findings are consistent with the limited evidence for dynamic cost shifting (Frakt 2011), aligning with mechanisms suggested by Garthwaite, Gross, and Notowidigdo (2018). However, prior studies do not examine immigration shocks or analyze the full range of financial margins through which hospitals adjust.

2. Institutional Background

This section summarizes the institutional features of U.S. immigration, health insurance, and hospital care that are most relevant for our analysis.

2.1. Immigration and Healthcare

The foreign-born population represents a large and geographically concentrated share of the U.S. population. As of 2025, approximately 53.3 million U.S. residents, or 15.8% of the population, were foreign-born, up from 9.6 million, or 4.6%, in 1970. Immigrants – a group that includes both unauthorized and authorized residents – are unevenly distributed across and within states, with especially large concentrations in California, Florida, and Texas.

Immigrants are less likely than native-born residents to have health insurance. The coverage rates are especially low among unauthorized immigrants, partly reflecting eligibility rules for public insurance.[5] Unauthorized immigrants are generally ineligible for Medicare, Medicaid, Childern's Health Insurance Program (CHIP), and Affordable Care Act (ACA) exchange plans, and many otherwise qualified immigrants face a five-year waiting period before becoming eligible for Medicaid.[6]

Several studies find that immigrants tend to arrive in better health than native-born residents, although this health advantage declines with time in the United States (see review in Cunningham et al. (2008) and NASEM (2015)). They also tend to use fewer healthcare services, consistent with

Duggan et al. (2023) show that privatizations of public hospitals are followed by increases in profitability and a decline in the quality of medical care.

[5] 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 legal status based on the respondents' reported demographic and socioeconomic characteristics. Hamilton et al. (2022) report that, within the 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.

[6] See details in Congretional Research Service (2022).

both better initial health and lower insurance coverage.[7] These findings suggest that immigration could affect the local healthcare system through its impact on both the overall demand for healthcare services and on patients' ability to pay (the latter determined by insurance status).

2.2. Uninsured Patients: Access to Healthcare and Funding Sources

Uninsured patients, regardless of immigration status, can obtain care through hospital emergency departments, hospital charity-care programs, Federally Qualified Health Centers (FQHCs), and privately funded free clinics. Hospitals with emergency departments are required by federal law to screen and stabilize patients with emergency medical conditions regardless of insurance status or ability to pay. After stabilizing treatment, patients may be admitted or transferred if further care is needed. Hospitals can bill patients for emergency services, but unpaid amounts become uncompensated care.

Hospitals' uncompensated care includes both charity care and bad debt. Charity care consists of free or discounted services provided to patients who qualify for financial assistance, while bad debt refers to billed services that patients do not pay. Coughlin et al. (2014) estimate that full-year uninsured individuals incurred $2,443 in per-capita medical spending in 2013, of which $500 was paid out of pocket. The remaining uncompensated portion was financed by governments, philanthropy, and the profits hospitals earn from privately insured patients.[8]

2.3. Hospital Organizational Forms and Charity Care

U.S. hospitals are organized as private nonprofit, for-profit, or public (government-owned) corporations, with nonprofits accounting for close to 60% of all hospital beds as of 2018. Online Appendix Figure A.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%.

As explained earlier, all hospitals with emergency departments must provide emergency care regardless of the patient's insurance status or ability to pay. Beyond this common obligation, nonprofit hospitals must provide community benefits, which include charity care, to maintain their

[7] See Guintella and Mazzonna (2015), Berk et al. (2000), Mohanty et al. (2005), Goldman et al. (2006). For example, Berk et al. (2000) report similar hospitalization rates but significantly lower rates of physician visits for undocumented Latino immigrants compared to the overall U.S. population.
[8] See also KFF (2021) Sources of payment for uncompensated care for the uninsured.

tax-exempt status.[9] For-profit hospitals do not face the same federal tax-exemption-based requirements, although some states impose charity-care obligations on all hospitals through licensing, Certificate-of-Need rules, or Financial Assistance Policies (Loutskina and Won, 2025).[10]

Public hospitals typically have broader statutory or mission-based mandates to serve low-income and uninsured patients than private nonprofits. Most public hospitals are owned and managed by state or local governments (counties or cities) and serve the general population.[11] They are funded directly through government budgets and can request additional funding as needs arise. They may also benefit more from federal payments to hospitals serving large low-income or Medicare populations, including Medicaid Disproportionate Share Hospital (DSH) payments and Medicare DSH adjustments.[12]

Overall, the three organizational forms differ in their missions, legal obligations, and access to funding. These differences suggest that immigration-induced increases in the need for uncompensated care will generate heterogeneous responses across hospital types. Private nonprofit hospitals, by virtue of their missions and tax-exempt status, are expected to help meet this need, but their ability to do so may be limited by available funding (see discussion in Section 3). Public hospitals face the strongest service obligations and have more direct access to government funding,

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[9] 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 hospitals, 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).

[10] 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 hospitals' charity care here: https://www.kff.org/health-costs/issue-brief/hospital-charity-care-how-it-works-and-why-it-matters/.

[11] A minority, such as Veterans Affairs (VA) or military hospitals, are owned by the federal government. An example of a local 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.

[12] Although private hospitals may also qualify for some of these payments, eligibility and allocation rules vary across states. 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.

which may make them best positioned to expand charity care. For-profit hospitals must provide emergency care, but, as value-maximizing firms, will avoid or exit unprofitable markets (though they may find it profitable to acquire nonprofits that end up in distress). We focus primarily on nonprofit hospitals, which account for the largest share of the sector, but also provide evidence on for-profit hospitals, public hospitals, and the hospital sector as a whole.

3. Framework for Analyzing the Effects of Immigration on Nonprofit Hospitals

In this section, we provide a simple framework for understanding how nonprofit hospitals respond to an economic shock—such as one induced by an immigration shock. Unlike for-profit hospitals, whose choices are disciplined by value maximization, nonprofit objectives are less clearly defined. Nonprofits often articulate broad missions (e.g., "providing healthcare to the local community") without specifying how they trade off service quality, affordability, or the provision of subsidized care to low-income patients.

A nonprofit's actual decisions nevertheless depend on its (unobserved) priorities and on constraints arising from the competitive environment in which it operates. To analyze nonprofit responses to a long-term economic shock, it is useful to impose the accounting identities that must hold for every nonprofit in each year. These identities allow us to trace the full range of feasible adjustments without assuming a particular objective function:

$$A_t = L_t + F_t \qquad \text{(Balance Sheet Identity)} \qquad (1)$$

$$\Delta A_t = \Delta L_t + \Delta F_t \qquad \text{(Change in Balance Sheet)} \qquad (2)$$

$$\Delta \mathrm{F_t} = \Pi_t \qquad \text{(Change in Fund Balances)} \qquad (3)$$

$$\Pi_t = R_t - C_t - Charity_t + Contributions_t \qquad \text{(Surplus)} \qquad (4)$$

where A_t denotes total assets, L_t liabilities, and F_t fund balances (analogous to equity). The surplus Π_t corresponds to net income; R_t is revenue; C_t includes all expenses except uncompensated care; $Charity_t$ captures uncompensated care (discounts to low-income patients, bad-debt write-offs); and $Contributions_t$ denotes grants and donations.[13]

[13] Note that hospital surpluses can also include other items, unrelated to the hospital's operations, such as gains and losses from financial investments. Moreover, depending on the applicable accounting standards, changes in fund balances could include other items that bypass the income statement, such as unrealized gains and losses.

The economic shock we study is a demographic shift resulting from an inflow of immigrant—and disproportionately uninsured—residents. One direct effect is a change in the hospital's optimal scale. If immigration reduces overall demand for healthcare services at prices the hospital is willing to accept, we should observe declines in assets, revenues, and investment. Prior literature (summarized in Section 2) finds that recent immigrants are younger and healthier and may induce some native out-migration, making this channel plausible.[14]

A second and more central channel operates through uncompensated care. Nonprofit hospitals are often expected—or required—to provide services to uninsured patients at prices below cost. Such obligations generate financial shortfalls, represented in Equation (4) as increases in $Charity_t$. Based on identities (1)–(4), hospitals can respond in one or more of the following ways:

1. Increase contributions ($Contributions_t$). Additional demand for subsidized care could, in principle, be financed by donors or taxpayers. Whether this occurs depends on their willingness to provide support and on the hospital's ability to access these funds. Information frictions may prevent hospitals from credibly conveying patient needs, and institutional frictions may limit access to public funding.

2. Increase revenues or reduce costs ($R_t - C_t$). Hospitals may attempt to raise margins elsewhere—by increasing prices or cutting costs. For instance, a financial shock may force an inefficiently run hospital to cut waste or to negotiate with insurers. Such strategies may be infeasible if the hospital lacks market power or faces strong competition. Alternatively, a hospital may shift resources away from other patients to subsidize care for the uninsured.

3. Increase liabilities (ΔL_t). Hospitals can temporarily finance shortfalls through debt issuance, effectively shifting resources from future to current patients. Persistent reliance on this strategy is unsustainable and increases the risk of financial distress.

4. Reduce assets (ΔA_t). Hospitals may scale down investment in financial or physical assets. Cuts in physical capital investment (or lower reinvestment rate) may reflect more efficient asset use or a reduction in the hospital's overall scale.

[14] 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 5.1.

Identities (1)–(4) must hold for all surviving hospitals. A nonprofit can weather a persistent financial shortfall if it begins with sufficient slack, such as accumulated financial assets, low liabilities, or an ability to reduce discretionary expenditures. Alternatively, a hospital may have been operating inefficiently prior to the shock, with the shock prompting operational improvements.

However, persistent shortfalls can also lead to market exit. A hospital unable to meet its obligations to creditors, employees, or suppliers may be forced to close, merge, or convert to for-profit status. We define all such outcomes as nonprofit exits. (We separately track acquisitions by nonprofit systems in which the hospital remains nonprofit but its control changes.) In a frictionless setting, closures would occur when the hospital's going-concern value to its community falls below the liquidation value; mergers or conversions occur when assets can be operated more efficiently under different ownership.

It is important to note that an immigration shock may trigger a nonprofit exit even when exit is not socially desirable. If the hospital generates net benefits for the community in its pre-shock state, allowing it to refuse or limit subsidized care might be preferable to liquidation. In practice, however, hospitals cannot simply maintain the status quo: federal law requires emergency care regardless of insurance status, and hospital administrators may view providing financial assistance as integral to the hospital's mission.

4. Identification

Our main tests estimate the causal effects of immigration on the real and financial outcomes of local hospitals described in Section 3. Identifying these effects is challenging because migration and healthcare are jointly determined and may be influenced by common underlying forces. For example, a local productivity shock that attracts new migrants could simultaneously expand the hospital sector by increasing employment, income, and insurance coverage, or by improving access to public or philanthropic funding. In such cases, immigration would be positively correlated with hospital growth even if immigration itself had no direct effect, biasing OLS estimates.

To address this endogeneity, we adopt the instrumental variables approach of Card (2001, 2009). The so-called "enclave" instrument is a Bartik-style instrument that exploits the tendency of newly arriving immigrants to settle in historical enclaves of co-nationals. We show below that this methodology is well-suited to studying healthcare markets and, when adapted to our context, allows us to circumvent several challenges that arise in labor-market applications (see the Online Appendix for details).

4.1. Baseline Regression

Our main tests are conducted at the county level, the smallest geographic unit for which both immigration flows and hospital outcomes can be reliably measured. The key explanatory variable is the inflow of new immigrants into county c between years t-x and t, scaled by the county's population in year t-x. We denote this measure by $M_{c,t}$. As a starting point, consider the following OLS regression:

$$\Delta Y_{c,t} = \beta M_{c,t} + \gamma X_{c,t-x} + \delta_{s,t} + \theta_m + \epsilon_{c,t}, \tag{5}$$

where $\Delta Y_{c,t}$ is a county-level outcome (e.g., the proportional change in hospital beds or hospital counts). The coefficient of interest, $\beta,$ captures the effect of immigration. $X_{c,t-x}$ denotes lagged controls, such as log county population, poverty rate, log median household income, and log number of hospital beds by ownership type. $\delta_{s,t}$ are state-by-period fixed effects that absorb state-level regulatory and economic shocks, and θ_m are county-type fixed effects based on metropolitan status.

Because each county contributes multiple time windows, the data form a panel of within-county changes. The specification allows us to test whether counties experiencing larger immigration inflows exhibit systematically different hospital trajectories. However, even with rich controls, concerns remain that unobserved economic shocks may drive both immigration and hospital growth.

4.2. Instrumental Variable

To address the endogeneity concerns, we construct an instrument that predicts immigration flows using the historical geographic distribution of immigrant communities. Immigrants of nationality f tend to settle disproportionately in counties where co-nationals were historically concentrated. For example, increases in immigration from the Dominican Republic should yield a larger inflow into Bronx County, NY, whereas increases from China should disproportionately raise inflows into San Francisco County, CA or Queens County, NY.

Formally, for a baseline Census year h, we compute for each country of origin f:

$$S_{c,f,h} = \frac{F_{c,f,h}}{A_{f,h}}, \tag{6}$$

where $F_{c,f,h}$ is the number of residents born in country *f* living in county c, and $A_{f,h}$ is the number of all U.S. residents born in country *f*. Using these shares, we predict the net inflow of immigrants into county *c* between *t-x* to *t*:

$$Z_{c,t} = \frac{\sum_f S_{c,f,h} * R_{f,t}}{P_{c,t-x}}, \tag{7}$$

where $R_{f,t}$ is the number of people born in country *f* relocating to the U.S. during *t-x* to *t*, and $P_{c,t-x}$ is the county's total population in year *t-x*. The instrument $Z_{c,t}$ therefore captures predicted inflows expressed as a fraction of the county's beginning-of-period population. Equipped with this instrument, we estimate the causal effects of immigration as follows:

$$M_{c,t} = \theta Z_{c,t} + \gamma X_{c,t-x} + \delta_{s,t} + \theta_m + \vartheta_{c,t} \tag{8}$$

$$\Delta Y_{c,t} = \beta \widehat{M}_{c,t} + \gamma X_{c,t-x} + \delta_{s,t} + \theta_m + \omega_{c,t}. \tag{9}$$

The exclusion restriction requires that $Z_{c,t}$ be uncorrelated with $\epsilon_{c,t}$. As emphasized in Goldsmith-Pinkham et al. (2020), violations arise if the exposure terms $S_{c,f,h}$ are correlated with future changes in hospital outcomes for reasons unrelated to immigration. In other words, counties historically exposed to immigrants from certain countries would need to experience systematically different hospital trajectories precisely when national inflows from those countries rise. Section 6.4 examines threats to identification in detail.

5. Data Sources and Summary Statistics

5.1. Data Sources

Our primary source of Census data is IPUMS USA. We use the 2000 Decennial Census (5% sample) to construct historical enclaves and the American Community Survey (ACS, 1% samples) for 2005–2019 to measure migration inflows.[15] Information on hospital organizational forms, system affiliations, and services comes from the American Hospital Association (AHA) Annual Survey Database. Financial variables are obtained from the Healthcare Cost Report Information System (HCRIS) and IRS Form 990 filings, which we access through the IRS and Candid. County-level uninsurance rates are drawn from the Small Area Health Insurance Estimates (SAHIE), supplemented by data on uninsurance among patients of Federally Qualified Health Centers (FQHCs). All variable definitions are in Appendix A.

5.2. 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 (2005-2015 through 2009-2019). As discussed below, the availability of immigration data restricts the sample to a subset of larger counties. Together, these counties account for more than 50% of the U.S. population and hospital bed capacity, nearly 80% of the foreign-born population, and about 10% of all U.S. counties. Following prior literature (Card 2009 and Goldsmith-Pinkham et al. 2020), we use ten-year windows to capture long-term effects; five-year windows are used in robustness tests. The overlapping windows help smooth inter-period volatility, and we also present results for each window separately.[16] We restrict the sample to counties identifiable in IPUMS, which excludes smaller counties, and require that a county have at least one hospital in the AHA directory at all relevant time points (excluding two counties).[17,18] The resulting panel consists of 1,625 county-period observations.

Table 1 presents descriptive statistics (stock variables as of *t-x*; flow variables as changes from *t-x* to *t*). The average county has 513,000 residents, 11.27% of whom are foreign-born. The average

[15] 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.
[16] This has been possible only in recent years, as the ACS provides yearly county-level birthplace data since 2005. 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).
[17] 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.
[18] In the main analysis, we consider all hospitals included in the AHA directory. 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.

uninsurance rate among individuals under 65 is 15.77%, rising to 29.76% among residents below 138% of the Federal Poverty Level (FPL). For lower-income populations served by FQHCs, the average uninsurance rate is 43.7%.[19]An average county experiences a ten-year immigrant inflow equal to 3.51% of its initial population. Predicted inflows average 3.09%, reflecting a tendency of smaller counties—where population growth is faster—to experience underprediction. Weighting counties by initial population raises both actual and predicted inflows to approximately 5%, eliminating the discrepancy (Panel B). Following the literature (e.g., Borjas 2006; Card 2009), we therefore weight regressions by beginning-of-period population and control for county size.

Every state in our sample contributes at least two counties (or ten county-windows), enabling the inclusion of state-period fixed effects. Counties are classified into five types based on their metropolitan status using Census definitions. County-type fixed effects allow for differential trends in migration and hospital outcomes across these groups.

Table 2 summarizes county-level AHA hospital characteristics. The average county has 7.3 hospitals and 1,604 beds: 342 in government hospitals, 998 in nonprofits, and 264 in for-profits. These ownership types differ in funding sources and charity-care obligations (Section 2), motivating our focus on heterogeneous responses. Panel B shows that total hospital beds increased by 1.7% per decade, driven by a 3.9% rise in for-profit beds, a 0.8% rise in nonprofit beds, and a 3.0% decline in government beds. These secular trends, plotted in Online Appendix Figure A.1, provide context for interpreting the magnitudes of our estimated effects.

5.3. Sample and Descriptive Statistics for the Hospital-Level Analysis

The hospital-level sample includes hospitals appearing in both the AHA and HCRIS datasets. We require non-missing observations in years *t* and *t-x* and require that hospitals maintain the same organizational form across the window. Because many federally funded government hospitals (especially VA hospitals) do not report to CMS, they are excluded. The final sample consists of 1,799 hospitals (8,021 hospital-window observations). For uncompensated-care analyses,

[19] There are approximately 1,300 FQHCs funded by the federal Health Resources and Services Administration (HRSA) in operation 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).

consistent data are available only from 2011 onward; therefore, these analyses use five-year windows and 5,100 observations.

Table 3 provides descriptive statistics. Nonprofit hospitals comprise 60% of the sample, for-profit hospitals 30%, and government hospitals 10%. Several differences across the organizational forms are worth noting. For-profit hospitals are significantly smaller (132 beds on average) than nonprofit (290 beds) and government hospitals (326 beds). Profit margins are lowest for government hospitals (0.8%), followed by nonprofits (3.7%), and highest for for-profits (7.8%). Government hospitals also serve disproportionately more Medicaid patients (29.2% versus 19.0% for nonprofits and 16.1% for for-profits) and devote the largest share of expenditures to uncompensated care (12.7% versus 6.5% and 5.7%, respectively). These differences align with the missions and financial structures typical of each organizational form.

The distribution of hospital profit margins also highlights the sector's financial fragility. While the median hospital margin is 4.37%, the 10th percentile margin is -6.19%, suggesting that many hospitals operate below or close to their break-even points. Such hospitals may be vulnerable to persistent financial shocks, such as increased demand for uncompensated care.

5.4. Immigration Patterns and Implications for the Instrument

Summary statistics in the Online Appendix illustrate how immigration patterns evolved over the sample period. The foreign-born share of the U.S. population rose steadily from 13.1% in 2005 to 14.6% in 2019. Appendix Figure A.2 breaks down inflows by country of origin and reveals substantial changes: while Mexico historically dominated, recent inflows increasingly originate from Asia (notably India and China). These patterns indicate that our instrument draws information from multiple national origin groups rather than being driven by a single large country. Section 6.4 confirms this by showing that the results are robust to excluding any major source country.

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

We begin the analysis at the county level, which is the smallest geographic unit at which we observe immigration flows. Following prior research, we examine changes over ten-year windows and weight each observation by the county's population in *t-x* (e.g., Borjas 2006; Card 2009). Unweighted regressions and estimates using five-year windows are discussed in the Online

Appendix and Section 6.4. Standard errors are clustered at the MSA level to account 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

We first examine how immigration affects county demographics, providing context for our main hospital-sector results. We focus on the county's native population, uninsurance rates, and household income, as shifts in these metrics directly influence the demand for healthcare services.

Demographic responses to immigration have been extensively studied. Standard labor-market models predict that immigration increases short-run labor supply, followed by long-run adjustments such as native out-migration or occupational shifts. The empirical literature generally supports these long-term adjustments. Our goal is merely to document these patterns in our setting.[20]

Table 4 presents the results. Column (1) reports the first-stage regression from Equation (8). The instrument strongly predicts immigration: a one-percentage-point increase in predicted inflows generates a 0.67 percentage point increase in actual inflows (first-stage F-statistic = 150). Column (2) shows that immigration has a negative but statistically insignificant effect on native population growth. The coefficient of -0.34 suggests that an inflow of 100 immigrants causes a net outflow of 34 native residents. The estimate is broadly consistent with Borjas (2006) and Card and Peri (2016), who report effects ranging from -0.66 to -0.10.

Columns (3)–(6) examine effects on 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, 2008-2018 and 2009-2019, due to the availability of insurance data. Although immigration has no significant effect on overall uninsurance, it significantly raises uninsurance among lower-income populations. A one–percentage-point increase in immigration raises uninsurance by 0.32 percentage points among residents below 138% of the Federal Poverty Level (FPL) and by 0.12 percentage points among those below 400% of FPL. These estimates align with prior evidence on the insurance status of foreign-born residents (Section 2).

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

Column (6) uses uninsurance data for patients of Federally Qualified Health Centers (FQHCs), which disproportionately serve low-income and uninsured populations. Immigration increases uninsurance in this sample by roughly one percentage point of the patient base—the largest effect across specifications. Online Appendix Table A.1 shows that immigration raises median household income and reduces poverty rates, consistent with prior findings (e.g., 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 newly arrived immigrants use fewer services than native residents who migrate away ("demand channel"). On the other hand, the adverse effects may have been mitigated by overall improvements in local economies or population growth resulting from immigrant flows. We quantify the combined effect of these forces on the hospital sector in Section 6.2 and examine specific channels in more detail in Section 7.

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

We next examine the effects of immigration—and the resulting rise in uninsurance rates—on the local hospital sector. As discussed earlier, hospitals may be required or may choose to provide care to uninsured patients at prices below cost, generating persistent financial shortfalls. If alternative funding sources are insufficient, hospitals may reduce investment, liquidate assets, or exit. These pressures may be amplified if local demand declines because immigrants are healthier than native residents who leave.

We begin with the county's total hospital bed capacity. This outcome is informative for three reasons: (i) beds are hospitals' core revenue-generating asset, so changes reflect investment, divestiture, or exit; (ii) bed data are available for the full AHA sample, unlike other investment measures;[21] and (iii) bed capacity captures the health sector's ability to care for patients and is therefore a key public-health metric.

[21] 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).

Table 5, Panel A, reports the results. The dependent variable in column (1) is the ten-year change in total beds, while columns (2)–(5) decompose beds by ownership type. In all columns, the changes are scaled by total beds (across all three hospital types) at the beginning of the ten-year period. The key explanatory variable is instrumented immigration measured over the ten-year horizon in percent of the county's beginning-of-period population. All regressions include county controls, state-year fixed effects, and county-type fixed effects. Standard errors are clustered on the MSA level.

The key finding is that immigration causes a substantial decline in county-level bed capacity. A one-percentage-point increase in immigration (as a fraction of total population) reduces total beds by 2.16%. This effect is entirely driven by nonprofit hospitals (column (3)), with no significant changes for government or for-profit hospitals.

The large magnitude of the response seems puzzling at first glance. 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 closures. Panel B examines this directly by studying changes in hospital counts. It shows that a one-percentage-point increase in immigration relative to the county's initial population reduces the total number of hospitals by 2.1%, driven almost entirely by nonprofit exits (-1.85%). For-profit hospitals show a small, statistically insignificant decline. In contrast, the number of government hospitals increases by 0.42%, suggesting that public hospitals absorb additional demand from both uninsured immigrants and insured native residents in areas where private hospitals exit.

To put these magnitudes in perspective, note that the average county experiences immigration inflow equal to 3.51% of its initial population over a ten-year window, with a standard deviation of 2.76 percentage points. Thus, a one-standard-deviation increase in inflow is associated with a 5.8% decline in the number of hospitals over ten years (= 2.76 × 2.1), corresponding to a reduction of about 0.4 hospital for the average county over ten years (= 7.25 hospitals × 5.8%). These magnitudes imply economically meaningful but plausible adjustments.

Table A.2 decomposes hospital-count changes into entries and exits.[22] Immigration increases exits—predominantly among nonprofits—and reduces entries in both the nonprofit and for-profit sectors (though the entry effects are statistically insignificant). Government hospitals show the opposite pattern, consistent with expanding local footprint, though the coefficients are not statistically significant.

Table A.3 presents OLS estimates using actual immigration rather than instrumented flows (Equation (5)). These regressions show generally weaker or insignificant effects. This is consistent with upward bias in OLS estimates: local economic growth may both attract immigrants and expand hospital demand. The discrepancy between the OLS and IV estimates tends to be smaller for public hospitals, possibly because of their weaker response to economic growth.

In sum, immigration significantly reduces local hospital bed capacity, driven by nonprofit exits. These results are consistent with both a decline in overall demand for hospital services and an increase in the uninsured share. The large responses along the extensive margin suggest that many nonprofits could not absorb persistent financial shortfalls by raising profits, drawing down assets, or making incremental investment adjustments. The heterogeneous responses across the three organizational forms align with their stated objectives and institutional constraints. Section 7 examines these mechanisms in hospital-level data.

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

The previous section documented that immigration leads to nonprofit exits, and there is also some evidence of expansions among government hospitals. We now examine how these differential responses shift market shares between private and public hospitals. Table 6 reports IV regressions analogous to those in Table 5, using changes in market shares as dependent variables. Market shares are based on private (that is, nonprofit and for-profit) hospitals' shares of beds, hospital counts, admissions, outpatient visits, and emergency room (ER) visits relative to all hospitals (the variables are changes in those shares from t-x to t).

[22] 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. Conversely, hospital entries are defined as events whereby new hospitals are established or existing hospitals are converted from a different organizational form. The second form of entry and exit is relevant only when we break down hospitals by organizational form (i.e., in columns 3-8).

Across specifications, immigration significantly reduces private hospitals' market shares. For example, a one–percentage-point increase in immigration reduces private hospitals' share of admissions by 0.74% (column 3) and ER visits by 0.88% (column 5); the effect on outpatient visits is −0.57% and statistically insignificant. Similar magnitudes for inpatient and ER visits may seem surprising, as 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 share.[23]

To summarize, immigration produces a durable shift in the ownership structure of local hospital markets: private hospitals' market shares decline, while government hospitals' shares increase. These patterns reverse long-standing national trends (Figure A.1) and are consistent with government hospitals stepping in to meet rising demand for subsidized care and to serve insured native residents in areas where private hospitals close.

6.4. Instrument Balance, Robustness Tests, and Refinements

6.4.1. Instrument Balance

Our identification assumption requires that, conditional on controls, the predicted migration flows $Z_{c,t}$ affect county outcomes $\Delta Y_{c,t}$ only through their effect on actual immigration. Although the exclusion restriction is fundamentally untestable, we present auxiliary evidence consistent with it being satisfied.

A standard diagnostic is whether the instrument is balanced with respect to the initial distribution of outcomes (Atanassov and Black 2016; Bennedsen et al. 2007). If the instrument is orthogonal to historical outcomes, this suggests that it is not proxying for long-standing differences across counties that could confound our estimates. We test for balance by regressing the number and market share of hospitals by organizational form in the year 2000 on the instrument averaged across the five ten-year windows. The specification includes demographic controls (income, population, and poverty rates) and fixed effects consistent with those in Table 5. As reported in Table 7, the instrument is only weakly correlated with these initial outcomes. The lack of

[23] Online Appendix Table A.4 shows that a 1% increase in immigration leads to an increase of 0.17% in government hospital admissions, though the effect is not statistically significant.

significance is not attributable to insufficient statistical power in the single-year cross-section: key demographic controls are significant at conventional levels (unreported). Moreover, in the robustness tests in the Online Appendix, IV estimates remain statistically significant even when using single, non-overlapping windows.

6.4.2. Robustness Tests

We conduct an extensive set of robustness checks, detailed in the Online Appendix, and summarize them briefly here. Across all tests, the main results—namely, that immigration reduces nonprofit hospital capacity and shifts market structure toward public provision—remain quantitatively and qualitatively unchanged. Specifically, our findings are robust to (1) excluding individual counties, as discussed by Young (2022), suggesting that no single county is pivotal for the results; (2) 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) using unweighted regressions rather than population-weighted regressions; (4) using 1990 as the historical Census enclave year in the calculation of the instrument rather than the year 2000; (5) using different immigration flow measures; (6) using the five ten-year windows separately; (7) using five-year windows rather than ten-year windows; (8) aggregating at the MSA level instead of the county level; (9) excluding Military and Veteran's hospitals; (10) using alternative approaches to construct the instrument, such as that proposed by Burchardi et al. (2026); (11) using alternative methods to construct standard errors following Adão, Kolesár, Morales (2019) and Borusyak, Hull, Jarael (2022).

6.4.3. Distinguishing Uninsured and Insured Immigration Inflows

In this section, we examine whether the main effects documented in Table 5 differ depending on immigrants' health insurance status.[24] Specifically, we use information reported in the

[24] An alternative potentially interesting distinction is between documented and undocumented immigration. We focus on immigrants' insurance coverage rather than their legal status for three reasons. First, from a hospital's perspective, a patient's insurance status is more relevant, as it directly affects their ability to pay. Second, prior literature (discussed in Section 2) finds that documented immigrants are less likely to have health insurance coverage compared to the general population, citing, for instance, waiting periods, labor-market frictions, or low take-up rates. Third, measures of undocumented immigration are noisy as they are typically constructed indirectly from administrative enforcement interactions or residual estimation procedures and may therefore capture variation in local enforcement intensity, policy priorities, or reporting behavior in addition to underlying legal status (e.g., Cascio et al. (2024), Cornaggia et al. (2024))

American Community Survey (ACS) to classify immigrants in our sample as insured or uninsured at the end of each measurement period. We then decompose total immigration inflows, $M_{c,t}$, into insured and uninsured components, $M^{I}_{c,t}$ and $M^{U}_{c,t}$, and repeat the main tests in Table 5, replacing total inflows with these two components. The predicted insured and uninsured inflows are constructed analogously to the baseline specification, using historical enclave shares interacted with national inflows of insured and uninsured immigrants by country of origin.

The results are reported in Online Appendix Table A.5, with additional estimation details provided in the table notes. The main finding is that both insured and uninsured inflows are associated with declines in hospital bed capacity, but the effects are substantially larger for uninsured inflows. This difference is especially pronounced for nonprofit hospitals. These findings suggest that uninsured inflows place greater financial pressure on hospitals than insured inflows, particularly on nonprofit hospitals, which are most exposed to obligations to provide uncompensated care, as discussed in Section 2.3.

Three caveats are in order. First, because the predicted insured and uninsured inflows use the same historical enclave shares, the two instruments are highly correlated, limiting our ability to cleanly disentangle their effects. They differ only through variation in the insurance composition of immigration flows across countries and over time. Second, while the first stage for uninsured inflows exceeds conventional thresholds, it is weaker than the first stage for insured inflows, suggesting that the estimates for uninsured inflows may be noisier. Third, an individual's insurance status is recorded at the end of the measurement period.[25] As a result, individuals classified as insured may have been uninsured during part of the window. This measurement issue likely adds noise and may bias downward our estimated uninsurance rates among recent immigrants.

For these reasons, we interpret the results in this section as suggestive. Nevertheless, the consistently larger effects associated with uninsured inflows support the view that increases in the uninsured population are an important mechanism behind hospital responses to immigration.

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[25] As explained in Appendix A, immigration inflows are computed using ACS data and include foreign-born individuals living in county c in year t who were not living in the United States ten years earlier. The ACS began reporting health insurance information in 2008. Because all of our ten-year measurement windows end after 2008, we can identify insurance status for all immigrants in our inflow measure at the end of each measurement window. The limitation, however, is that the ACS does not report changes in an individual's insurance status over time. Thus, individuals classified as insured in year t may have been uninsured earlier in the measurement period. As a result, our estimates are noisy and likely understate uninsurance rates among recent immigrants.

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

We now examine how individual hospitals respond to immigration-induced shocks, focusing on hospitals that survive over the measurement window. As shown in Section 6, immigration does not significantly alter the size of the native population but increases the share of newly arrived—and disproportionately uninsured—residents. As discussed in Section 3, these shifts may affect hospitals through two channels: a reduction in overall demand for healthcare services and an increase in uncompensated care. This section analyzes how these forces affect hospitals' profitability, investment, financing, and survival.

7.1. The Effects on Profit Margins and Spending on Uncompensated Care

We begin by examining hospitals' profitability. Our main measure is the profit margin, defined as net income divided by revenue. Net income, as reported in hospitals' statements of revenues, incorporates uncompensated care expenditures, so increases in uncompensated care should directly reduce margins.[26] It also includes revenue from donations and government grants. Thus, if immigration has no effect on margins, hospitals must be offsetting immigration-related losses either through higher profits elsewhere or through increased contributions. A negative effect, by contrast, indicates that these offsetting mechanisms are insufficient.

Table 8 reports the results for all hospitals (Panels A-B) and hospitals split by type (Panels C-E). We examine both ten-year and five-year windows and require non-missing hospital data in both year *t* and *t-x*, with organizational form held constant. Because uncompensated care data are consistently available only starting in 2011, analyses involving uncompensated care use five-year windows. Regressions are unweighted, as larger counties contribute more hospital observations.

The key finding is that immigration significantly reduces hospital profit margins. The coefficients on *ΔMargin (%)* are -0.30 in Panel A (ten-year windows) and -0.49 in Panel B (five-year windows), both statistically significant. As a placebo test, both panels test whether immigration increases Medicaid admissions—a potential cause of declining margins in a local downturn. Because recent or undocumented immigrants typically do not qualify for Medicaid

[26] 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.

(Section 2), immigration should not affect Medicaid shares. Consistent with this prediction, we find no significant effect on Medicaid admissions. This supports the interpretation that margin declines are driven specifically by uncompensated care rather than by a broader economic contraction.

Importantly, Panel B (column 4) shows that uncompensated care increases significantly in response to immigration. Uncompensated care expenditures are scaled by revenue to permit direct comparison with margin effects. The coefficient on uncompensated care (0.64) is larger in magnitude than that for profit margins (-0.49), suggesting some offsetting profit increases. However, unreported tests indicate that the difference between these effects is not statistically significant. As shown in the Online Appendix Table A.6, neither private donations nor government grants increase in response to greater immigration, consistent with hospitals lacking external funding to offset these shocks.

In the remaining panels, we split hospitals by their organizational forms. The regressions in Panel C 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 E). Interestingly, there is also some evidence of declines in Medicaid admissions (Panel D). 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. 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.

To put the magnitudes of the margin effects in perspective, a one-percentage-point increase in immigration lowers margins by 0.37 percentage points for nonprofit hospitals (column (2) in Panel C). This estimate implies a decline of 1.0% due to a one-standard-deviaiton increase in immigration inflow (= 2.76%). As a comparison, the average margin in Table 3 is 3.66%. These estimates are large but economically plausible. Thus, consistent with the county-level results, immigration appears to create significant financial pressure on nonprofit hospitals. The next section explores how nonprofits respond to this pressure.

7.2. Nonprofit Hospitals' Funding Sources: Investment and Financing

We next examine how nonprofit hospitals finance the immigration-induced shortfalls documented above. Section 3 outlined the accounting identities that constrain nonprofit responses: persistent declines in profits reduce retained surpluses, and because nonprofits cannot raise equity, they must adjust by increasing liabilities or reducing assets. The preferred adjustment may depend on whether immigration also reduces demand for healthcare services, in which case downsizing may be efficient.

Table 9 reports full-sample results; heterogeneous responses appear in Table 10 and Online Appendix Table A.7. Based on Table 9, nonprofit hospitals respond to immigration by reducing investment in fixed assets and, to a lesser extent, increasing liabilities, though only the former effect is statistically significant. Column (2) shows that fixed assets decline by 2% for every one–percentage point increase in immigration. Notably, surviving nonprofits do not reduce bed capacity, consistent with county-level results showing that aggregate declines in bed capacity are driven by nonprofit exits rather than contractions among surviving facilities. Because fixed assets reflect investments in buildings, equipment, and long-lived capital, the decline suggests that nonprofits shift resources away from future patients to meet the immediate needs for subsidized care.

Turning to the subsample results, we find evidence that hospitals' responses are heterogeneous in ways that make economic sense. Online Appendix Table A.7 (Panel A) shows that system hospitals exhibit little decline in fund balances, consistent with the possibility of intra-system transfers that offset reduced retained earnings. Standalone hospitals, by contrast, experience declines in fund balances and increases in liabilities (though effects are not statistically significant). These differences align with the notion that system hospitals can spread shocks across affiliated entities, while standalone hospitals cannot. Online Appendix Table A.7 (Panel B) shows similar effects across small and large hospitals, suggesting that size is not a strong predictor of hospitals' financial responses.

The most striking results are in Table 10, where we split hospitals based on their location in a more populous versus less populous county. Hospitals in more populous counties experience much larger declines in profit margins and correspondingly large, statistically significant reductions in fund balances, total assets, and fixed assets. Their liabilities also increase, resulting in significantly higher leverage ratios. Online Appendix Table A.8 shows that these counties are far more competitive (HHI of 1500 versus 3900), consistent with hospitals in competitive markets being less able to pass through losses to patients or insurers or to adjust quality. The heterogeneous effects could also be caused by differences across counties in the type of immigrants that respond to the instrument.[27]

While fully identifying the mechanisms behind these differences is beyond the scope of this paper, the broader implication is that average effects mask substantial heterogeneity, with hospitals' responses shaped by system affiliation, competition, and their ability to transfer or absorb financial shocks.

7.3. Components of Uncompensated Care: Charity Care Versus Bad Debt

The previous section examines hospitals' total spending on uncompensated care. As explained in Section 2.2 and Appendix A, uncompensated care consists of two components: charity care, defined as free or discounted services provided to patients who qualify for financial assistance, and bad debt, defined as billed services that patients do not pay. Our main tests in Table 8 use the combined measure because immigration could plausibly affect both components. Moreover, prior work reports that hospitals have discretion in classifying expenditures as either charity care or bad debt, so the distinction may not be clean-cut.[28] This section explores whether immigration affects the two components differently.

To do so, we estimate regressions similar to those in Table 8, Panel E, but use changes in charity care and bad debt separately as dependent variables. Online Appendix Table A.9, Panel A, reports descriptive statistics, and Panel B reports second-stage regressions by hospital type. We find that instrumented immigration inflows are positively associated with both components of uncompensated care, and that both coefficients are statistically significant for public hospitals. For private nonprofits, only the charity-care component is statistically significant at conventional levels, while for for-profit hospitals, neither component is significant. These results suggest that

[27] 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.
[28] Beck et al. (2021) report evidence that nonprofit hospitals shift costs from bad debt to charity care prior to public bond issuance. Huang, Kumar, and Wange (2026) show that nonprofit hospitals reduce charity care in response to regulations that make debt collection more difficult.

immigration inflows can affect hospitals' profit margins through both higher spending on financial assistance and a larger burden from unpaid bills. They also reinforce the earlier finding that for-profit hospitals are least likely to increase spending on uncompensated care.

7.4. 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 hospital-by-decade panel similar to Table 9, with two differences: (i) acquisition and closure data come from Lewellen et al. (2025), whose panel ends in 2018 and includes only nonprofit and for-profit hospitals with assets and revenues of at least $1 million; and (ii) we no longer require that the organizational form remain constant, allowing us to capture conversion events. For closure analysis, we also drop the survival requirement.

Table 11 reports the results. Panel A examines acquisitions by all systems (columns 2–4), nonprofit systems (columns 5–7), and for-profit systems (columns 8–10), with samples further split by target ownership.[29] The key finding is that immigration increases the likelihood of nonprofit hospitals being acquired, and this effect is driven entirely by acquisitions by for-profit systems. Column (9) shows that a one–percentage-point increase in immigration increases nonprofit acquisitions by for-profit systems by 2.3 percentage points, relative to a baseline acquisition frequency of 8% (6% among nonprofit targets). Because acquisitions by for-profit systems typically lead to conversion, these events account for part of the nonprofit exit response documented in Section 6.

Panel B shows that both nonprofit and for-profit hospitals become more likely to close as immigration increases. A one-percentage-point increase in immigration raises closures by 0.6 percentage points for nonprofits and 0.7 percentage points for for-profits, relative to baseline frequencies of 1.4% and 3.3%, respectively. Thus, while the unconditional effects are similar, the

[29] 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).

proportional effect is substantially larger for nonprofits, with closure rates increasing by roughly 43% for nonprofits compared to about 21% for for-profit hospitals. Unreported regressions show similar patterns for mergers: nonprofit exits via mergers increase significantly, whereas for-profit mergers do not.

These results reinforce the conclusion that immigration-induced financial pressure leads to asset reallocation through both closures and ownership changes. The demographic shifts pose a challenge to both nonprofits and for-profits, but their responses differ. While for-profit hospitals exhibit higher closure rates, they are also more likely to acquire nonprofit assets. Moreover, surviving for-profits remain profitable, suggesting a greater ability to limit subsidized care or adapt in other ways. In contrast, nonprofit hospitals experience higher exit rates through closures or mergers and, conditional on survival, declining margins. These patterns are consistent with nonprofits' more stringent financial and mission-driven constraints.

8. Mechanisms and Implications: Discussion

One of our central findings is that immigration causes local hospital sectors to contract. As discussed in the introduction and Section 2, this contraction could arise through multiple channels. We organize these mechanisms into two broad categories. The first is the uninsurance channel, which operates through a decline in health insurance coverage among the local patient population. The second is the demand channel, which operates through changes in the overall demand for healthcare services, for example, if recent immigrants use less healthcare than native residents who leave high-immigration areas. Both channels may be present. However, the evidence points to the uninsurance channel as an important mechanism behind our results.

Several pieces of evidence support this interpretation. First, the regressions in Table 4 show that immigration increases the share of uninsured residents in a county, especially among lower-income populations and patients served by Federally Qualified Health Centers. These findings are consistent with prior evidence on immigrants' lower rates of health insurance coverage and with institutional limits on immigrants' access to public insurance programs, including Medicaid and ACA coverage. Second, the hospital-level evidence in Table 8 shows that immigration increases hospital spending on uncompensated care, including charity care and bad debt. These effects are concentrated among public and private nonprofit hospitals, consistent with these hospitals treating a larger share of patients who are uninsured or unable to pay. Third, when we decompose immigration inflows into likely insured and likely uninsured inflows, we find substantially stronger effects for uninsured inflows.

The heterogeneous responses across organizational forms provide further support for the uninsurance channel. Public hospitals, which face the strongest service obligations and can draw on public budgetary support, experience the largest increases in uncompensated care and the largest declines in profit margins. Private nonprofit hospitals may face similar mission-based and tax-exemption-based expectations to provide subsidized care, but their ability to meet this need may be limited by their access to external funding and internally generated cash flows. Consistent with this interpretation, nonprofit hospitals are more likely to exit through closures or acquisitions. For-profit hospitals, by contrast, show weaker responses in uncompensated care and profit margins, consistent with their weaker charity-care obligations and greater ability and willingness to avoid unprofitable operations.

It is important to note that our evidence does not rule out alternative channels. In particular, immigration could affect hospitals by changing the overall demand for healthcare services. If immigration induces some native residents to move away, and if recent immigrants are initially healthier or use less healthcare than the residents they replace, then hospitals may experience a decline in demand even in the absence of a change in insurance coverage. This demand channel could contribute to the contraction in hospital capacity and to lower margins. However, by itself, it is less able to explain three patterns in the data: the sharp differences across organizational forms, the significant increases in uncompensated care, and the stronger effects of uninsured relative to insured immigrant inflows. Moreover, our estimate of native out-migration is economically modest and statistically insignificant. Thus, while the demand channel may contribute to the overall effect, it does not appear to be the main force behind our findings.

We also consider whether the results could reflect broader local economic contraction rather than immigration-induced financial pressure on hospitals. Two pieces of evidence speak against this interpretation. First, immigration does not appear to depress local economic conditions in our sample; if anything, local income rises following immigrant inflows. Second, we find no corresponding increase in Medicaid admissions but do find significant increases in uncompensated care. This pattern is difficult to reconcile with a general deterioration in local economic conditions, which would likely increase reliance on Medicaid and other public insurance programs. Instead, it is more consistent with a shift toward uninsured patients whose care is not fully reimbursed.

Overall, while we cannot rule out every alternative mechanism, much of the evidence is consistent with the uninsurance channel as a key explanation. Interpreted this way, the paper's implications extend beyond immigration. Immigration provides a useful empirical setting for studying how hospitals respond to persistent increases in local demand for subsidized care – shocks that could also arise from demographic change, economic dislocation, changes in insurance coverage, or public policy reforms. Such shocks are difficult to isolate in general because they often coincide with changes in local economic conditions, government funding, and patient demand. The enclave-based design provides a useful setting to study their effects. Moreover, shocks caused by economic crises tend to be shorter-lived, making immigration especially useful for studying more persistent shifts in local demand for subsidized care.

Interpreted through this lens, our results show how hospitals respond to rising demand for uncompensated care. These responses depend crucially on both hospitals' legal and mission-driven obligations and the resources available to support those obligations. Public hospitals absorb a larger share of uncompensated care while remaining in the market. For-profit hospitals appear to limit exposure to unprofitable activities but participate in the reallocation of distressed assets through acquisitions. Nonprofit hospitals absorb part of the burden and adjust through reduced investment, acquisitions, conversions, or closures. These patterns do not provide a general evaluation of alternative ownership forms. Instead, they illustrate how organizations with different missions, constraints, and funding sources respond to a common shock.

9. Conclusions

Immigration has been a major driver of U.S. population growth, with its effects concentrated in specific geographic areas. This paper examines how immigration affects local hospital sectors. Understanding these effects is important for public policy and offers a unique setting for studying how nonprofit hospitals respond to large, persistent economic shocks. We focus on nonprofits both because they account for the majority of U.S. hospital beds and because their objectives and financial constraints remain less well understood.

To identify the effects of immigration, we employ the historical-enclave instrument widely used in the immigration literature. The approach exploits the tendency of new immigrants to settle in areas with preexisting concentrations of co-nationals, using national-level shocks to immigration as a source of plausibly exogenous variation in local inflows.

Our results show that immigration significantly reduces local hospital bed capacity, driven primarily by exits of nonprofit hospitals—through closures or acquisitions by for-profit systems. Government hospitals expand market shares, producing a systematic shift in local ownership structures toward public provision. These aggregate patterns are mirrored in hospital-level financial data: surviving nonprofits experience sizable declines in profit margins and sharp increases in uncompensated care. In response, they cut capital investment or, in some cases, exit entirely. These adjustments are especially pronounced in densely populated markets, where competitive pressures may limit hospitals' ability to offset financial losses.

Overall, immigration exerts a meaningful and lasting impact on the local healthcare sector, shrinking its scale and shifting activity from private nonprofits to public hospitals. By tracing the mechanisms behind these adjustments, the paper contributes to our understanding of the economics of nonprofit hospitals. Although nonprofits tend to absorb a disproportionate share of the increased "need" for subsidized care (compared to for-profits), they often struggle to offset the resulting financial shortfalls. Consequently, they respond through investment reductions, ownership conversions, or closure. These findings underscore the central role of profit-generating activity in enabling nonprofit hospitals to sustain their mission-driven goals.

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Appendix A

Appendix Section 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.
County types	Counties are classified into five types based on their metropolitan status using Census definitions: central counties in large metropolitan areas, peripheral counties in large metropolitan areas, counties in smaller metropolitan areas, mixed metropolitan counties, and non-metropolitan counties outside MSAs.
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.
Imm. Inflow (Insured or Uninsured) (%)	Ten-year insured (or uninsured) immigration inflow into a county from *t-10* to *t* in percent of the county's population in *t-10*. Insured immigration inflow from *t-10* to *t* is the number of insured 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. Insurance status is measured in year *t* using ACS health insurance information. Immigration year is based on the Census variable "YRIMMIG."
Pred. Imm. Inflow (Insured) (%)	Predicted ten-year insured immigration inflow. It is constructed as the sum of the products of country-level inflows of insured individuals, $R^{I}_{f,t}$, where insurance status is measured as of year t, and historical enclave shares, $S_{c,f,h}$, scaled by the county's population at the beginning of the window.
Pred. Imm. Inflow (Uninsured) (%)	Predicted ten-year uninsured immigration inflow. It is constructed as the sum of the products of country-level inflows of uninsured individuals, $R^{U}_{f,t}$, where insurance status is measured as of year t, and historical enclave shares, $S_{c,f,h}$, scaled by the county's population at the beginning of the window.
Variables from the SAIPE database (County-level)	

Household Income ($000)	Median household income in thousands.
Poverty (%)	The 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. Available since 2008.
Uninsured % (<138% FPL)	The percentage of a county's population below 65 years old and 138% of the Federal Poverty Line without health insurance. Available since 2008.
Uninsured % (<400% FPL)	The percentage of a county's population below 65 years old and 400% of the Federal Poverty Line without health insurance. Available since 2008.
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* $\log(\text{'var'})_t - \log(\text{'var'})_{t-x}$. *Changes in ratios are* $\text{'var'}_t - \text{'var'}_{t-x}$. *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 (%)	Uncompensated care / Total revenue. Uncompensated care is constructed using data from Worksheet S-10 of HCRIS. We use total uncompensated care (Line 30), which includes both charity care and bad debt, and has been reported consistently since 2011. If the ratio is outside the [0,1] interval, it is assigned a missing value.
Charity Care (%)	Charity care / Total revenue. Charity care is the cost of charity care is reported on Worksheet S-10, Line 23, and has been reported consistently since 2011. If the ratio is outside the [0,1] interval, it is assigned a missing value.
Bad Debt (%)	(Bad debt / Total revenue) = (Uncompensated care / Total revenue) – (Charity care / Total revenue). Missing if (Uncompensated care / Total revenue) or (Charity care / Total revenue) is missing, or if the ratio is outside the [0,1] interval.
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, 2026). 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.

Table 1

Descriptive Statistics for County-Level Demographic Data

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 (%)	3.09	0.72	2.01	6.37	3.10	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 (%)	5.25	1.31	4.05	11.59	4.11	1,625

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*.

Table 2

Descriptive Statistics for County-Level Hospital Data

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
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

Panel B: Changes over the measurement period

	Mean	P10	P50	P90	SD	N
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

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*. Variable definitions are in Appendix A.

Table 3

Descriptive Statistics for Hospital Data

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 (%)	6.89	1.87	5.47	12.62	6.26	5,100
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 (%)	0.77	-13.86	0.99	14.83	12.09	0.77
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 (%)	0.63	-4.77	0.22	6.21	4.84	5,100

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. (%)	12.748	6.484	5.669	6.264***	7.079***	0.815
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 (%)	0.59	0.69	0.98	-0.10	-0.39	-0.29
ΔLeverage (%)	5.324	-4.683	-6.783	10.007***	12.108***	2.100
ΔUncomp.(%)	0.722	0.143	1.994	0.580	-1.271	-1.851***

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 1,799 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*. Panel C compares the hospital-level variables in *t-x* across organizational forms. Variable definitions are in Appendix A. Standard errors in Panel C are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Table 4

The Effects of Immigration on County-Level Demographic Outcomes

Dependent Var.:	Imm. Inflow (%)	Native Net Flow (%)	ΔUninsured (%)			
			All Income	<400% FPL	<138% FPL	FQHC Visits
	(1)	(2)	(3)	(4)	(5)	(6)
Imm. Inflow (%)		-0.343	0.043	0.117**	0.313***	1.006***
		(0.363)	(0.035)	(0.048)	(0.049)	(0.371)
Pred. Imm. Inflow (%)	0.667***					
	(0.055)					
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	149.7					

The table shows regressions of the county-level demographic outcomes on instrumented immigration flows. Column (1) shows the first-stage regression (Equation 8) 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 9). *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 (FPL); in column (6) the uninsurance rate is for patients of the Federally Qualified Health 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%.

Table 5

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

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 (%)	-2.160**	0.240	-2.166***	-0.233	-2.399***
	(0.996)	(0.368)	(0.541)	(0.547)	(0.917)
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 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 (%)	-2.100***	0.417*	-1.849**	-0.668	-2.517***
	(0.659)	(0.237)	(0.906)	(0.440)	(0.801)
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

The table shows 2SLS 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*. Control variables in Panel A include *Log(Population), Log(Household Inc.), Poverty (%), Top 50 Metro Area, Log (FP Beds), Log(NP Beds), Log(GOV Beds), % Private Beds*. Control variables in Panel B 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%.

Table 6

The Effects of Immigration on Private Hospitals' Market Shares

Dep. Variables:	(1) ΔPrivate Beds Share (%)	(2) ΔPrivate Hosp Share (%)	(3) ΔPrivate Adm. Share (%)	(4) ΔPrivate Outp. Share (%)	(5) ΔPrivate ER Share (%)
Imm. Inflow (%)	-0.771**	-1.108***	-0.744***	-0.567	-0.880***
	(0.330)	(0.406)	(0.252)	(0.405)	(0.296)
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	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}

The table shows 2SLS 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%.

Table 7

Instrument Validity

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 (%)	0.069	0.042	-0.111	-0.047	-0.017	-0.073*
	(0.431)	(0.538)	(0.394)	(0.073)	(0.032)	(0.042)
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

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)*, *Poverty (%), and Top 50 Metro Area* 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%.

Table 8

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

Panel A: All hospitals over ten-year periods

Dep. Variables:	(1) Imm. Inflow (%)	(2) ΔMargin (%)	(3) ΔMedicaid (%)
Imm. Inflow (%)		-0.300*	0.057
		(0.154)	(0.249)
Pred. Imm. Inflow (%)	0.655***		
	(0.059)		
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	124.6		

Panel B: All hospitals over five-year periods

Dep. Variables:	(1) Imm. Inflow (%)	(2) ΔMargin (%)	(3) ΔMedicaid (%)	(4) ΔUncomp. (%)
Imm. Inflow (%)		-0.493***	0.100	0.644***
		(0.151)	(0.264)	(0.178)
Pred. Imm. Inflow (%)	0.649***			
	(0.050)			
Observations	19,074	18,286	19,075	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	169.8			

The table presents 2SLS 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. Control variables at the geographic level are the same as for Table 5, Panel A. Additional hospital-level controls include indicators for nonprofit and government hospital status, Margin (%), Medicaid (%), Log(Beds), and System in t-10. 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%.

Table 8, cont.

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 (%)	-1.311**	-0.368**	0.550	-2.192**	-0.465**	0.012
	(0.663)	(0.188)	(0.346)	(1.052)	(0.215)	(0.428)
Observations	720	4,682	2,286	1,687	10,864	5,735
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}

Panel D: Medicaid regressions by organization form

Dep. Variable:	ΔMedicaid (%)					
Sample:	GOV	NP	FP	GOV	NP	FP
Imm. Inflow (%)	-0.929**	0.143	0.067	-0.127	0.138	0.148
	(0.372)	(0.197)	(0.372)	(0.654)	(0.209)	(0.333)
Observations	770	4,845	2,406	1,800	11,233	6,042
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}

Panel E: Uncompensated care regressions by organization form

Dep. Variable:	ΔUncompensated (%)					
Sample:				GOV	NP	FP
Imm. Inflow (%)				2.046***	0.303**	0.341
				(0.595)	(0.141)	(0.245)
Observations				487	3,425	1,188
State-year FE				Yes	Yes	Yes
County-type FE				Yes	Yes	Yes
Reg. Stage				2^{nd}	2^{nd}	2^{nd}

Table 9

The Effects of Immigration on Nonprofit Hospital Investment and Financing

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 (%)	-0.625	-1.951**	0.431	-0.358	0.679	-0.100
	(0.932)	(0.922)	(0.831)	(1.967)	(1.448)	(0.552)
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	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}

The table shows 2SLS 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 total assets, fixed assets, number of beds, fund balances, and 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 8, 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 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%.

Table 10

Nonprofit Hospital Investment and Financing by County Size

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 (%)	-7.546**	-5.496**	-1.663	-19.563***	3.015	2.917*	-1.690***
	(3.404)	(2.338)	(1.198)	(5.897)	(5.358)	(1.567)	(0.616)
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 (%)	1.429	-0.094	0.801	2.647	-0.697	-0.534	0.041
	(1.215)	(0.907)	(0.973)	(3.525)	(1.059)	(0.433)	(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

The table shows 2SLS 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 total assets, fixed assets, number of beds, fund balances, and 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 8, 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 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%.

Table 11

The Effects of Immigration on Hospital Acquisitions and Closures

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 (%)		0.011*	0.015*	-0.010	-0.006	-0.007	-0.006	0.017***	0.023***	-0.008
		(0.006)	(0.008)	(0.011)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.011)
Pred. Imm. Inflow (%)	0.686***									
	(0.060)									
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	130.5									

Table 11

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 (%)	0.006***	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	2^{nd}	2^{nd}	2^{nd}

The table shows 2SLS 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 are the same as in Table 8, 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%.

Online Appendix Section A: Robustness Checks

A.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.3. 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.

A.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. To do so, we reconstruct the predicted and actual share of immigrants excluding each of these groups, one at a time. Table A.10 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.

A.3 Unweighted 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.11, columns 1 and 2, and find similar results. Overall, our results are similar across different weighting schemes.

A.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.11, columns 3-4. As expected, the first-stage regression is significantly weaker, with an F-test of 18.5. 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.

A.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 who 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, 2026) and Card and Peri (2016)).

For completeness, we replicate our main county-level tests using the alternative approach and report the results in the Online Appendix Table A.11, 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 A.11 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.

A.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.12 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 changes in nonprofit bed capacity does not follow a monotonic pattern over the years: the coefficient is highest in the 2005-2015, 2006-2016, and 2009-2019 windows, and lowest in the 2008-2018 window. Overall, the tests confirm that our results are not driven by a particular window.

A.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.13 presents results from regressions estimated across 10 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.13 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.13). Moreover, unlike in the earlier studies, the immigration patterns shift significantly during our sample period (as shown in Figure A.2), which mitigates the concern that predicted migration captures the effects of past migration.

A.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., 2026; 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.14 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 1.75% decline in the overall number of hospital beds, which is similar to the 2.16% decline estimated at 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.

A.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 consists mostly of locally funded hospitals (i.e., county- or state-funded). Table A.15 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.

A.10 Alternative Instruments

Burchardi et al. (2019, 2026) 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 7). 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 from a more distant past to construct the enclaves (see Online Appendix Table A.11). 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, but the recent immigration flows have shifted toward Asian immigrants (Figure A.2). Moreover, we show that excluding each of the three largest immigrant groups does not affect the main findings (Online Appendix Table A.10).

Nevertheless, we perform additional robustness tests using Burchardi et al.'s (2026) instrument (Online Appendix, Table A.16). 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. (2026) examine unscaled immigration flows (that is, flows in thousands of people) and construct their instrument using absolute numbers of immigrants.[30] Therefore, in the Online Appendix, Table A.16, Panel A, we show for comparison results using both the original Burchardi et al. (2026) instrument (*IIG Instrument (000)*) and using their instrument scaled by the counties' populations (*IIG Instrument (%)*).[31] 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. (2026) 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 (2026) 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 (2026) approach, that is, using absolute rather than relative immigration flows. In Table A.16, Panel B, we use their instrument (unscaled) alongside our immigration 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-

[30] 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.

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

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.

A.11 Robustness of Standard Errors

Adão, Kolesár, and Morales (2019) show that conventional inference procedures can be misleading in shift-share designs, including Bartik and enclave-based instruments, because the identifying variation ultimately comes from a limited set of aggregate shocks that are shared across many observations. In our setting, immigration inflows into different counties are partly driven by the same national-origin shocks—such as aggregate inflows from Mexico, India, or China—interacted with counties' historical enclave shares. As a result, counties exposed to similar immigrant-origin compositions are not independent observations, even after controlling for geography or clustering at broader geographic levels such as metropolitan statistical areas. Intuitively, standard inference procedures may overstate the effective sample size because many county-level observations load on the same underlying immigration shocks.

To address these concerns, we implement two complementary inference approaches. First, we follow the methodology of Adão, Kolesár, and Morales (AKM), which adjusts standard errors to account for correlation across counties induced by common origin-country shocks. Under this approach, the regression is still estimated at the county level, and the number of observations remains unchanged, but inference reflects the effective variation coming from the underlying shocks. Specifically, AKM uses a sandwich variance estimator that aggregates exposure-weighted residuals at the origin-country level.

Second, we implement the Borusyak–Hull–Jaravel (2025) (BHJ) approach, which re-expresses the estimation at the level of the underlying shocks. In our setting, this involves transforming the data to the origin-country-by-window level using counties' historical enclave shares as exposure weights. The transformation aggregates county-level outcomes according to their differential exposure to national immigration inflows from each origin country. As a result, inference is conducted using variation across the underlying origin-country shocks while preserving the exposure structure that generates identifying variation in the shift-share design. In practice, AKM can be viewed as correcting inference while preserving the original county-level specification, whereas BHJ re-expresses the estimation in terms of the underlying shocks that drive the instrument.

Table A.17, Panel A, replicates the main results of Table 5 using the AKM methodology. The standard errors are substantially smaller under AKM than in our baseline specification. This suggests that our baseline standard errors do not understate statistical uncertainty arising from cross-county correlation in the shift-share structure and, if anything, may be conservative in this setting.

To replicate the main results using the BHJ methodology, we make several adjustments. First, the unit of observation becomes the origin-country-by-window rather than the county-by-window, because the data are aggregated to the origin-country level. Second, the population scaling used in our main analysis varies across windows because immigration inflows are scaled by each county's beginning-of-window population. This scaling breaks the equivalence between our baseline specification and the BHJ-transformed data constructed at the origin-country-by-window level. We therefore modify the baseline specification so that all windows are scaled by the same initial county population.

Panel B presents our main estimates using county-level windows, now scaled and weighted by each county's population at the beginning of the first window, 2005. Panel C then applies the BHJ transformation and estimates the model at the origin-country-by-window level, reducing the sample from 1,625 observations to 565 observations. Although there are 134 countries of foreign origin, not all of them are present in the historical year 2000 or in every measurement window, so the total number of observations is less than $134 \times 5 = 670$. The coefficients in Panels B and C are nearly identical, confirming that the data transformation is inconsequential to the parameter coefficients. Crucially, the standard errors are smaller under the BHJ methodology than in our baseline specification, confirming the pattern observed under the AKM approach.

Overall, these results indicate that our findings are robust to alternative inference procedures that account for the dependence structures induced by shift-share designs. Across both AKM and BHJ approaches, the estimated effects remain similar, and the adjusted standard errors do not weaken our statistical conclusions.

Online Appendix Section B: Additional Tables and Figures

Table A.1: The Effects of Immigration on County-Level Income and Poverty

Dependent Var.:	(1) ΔHousehold Income (%)	(2) ΔPoverty Rate (%)
Imm. Inflow (%)	1.479**	-0.130**
	(0.660)	(0.052)
Observations	1,625	1,625
State-year FE	Yes	Yes
County-type FE	Yes	Yes
Controls	Yes	Yes
Reg. Stage	2nd	2nd

The table shows 2SLS 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%.

Table A.2: The Effects of Immigration on Hospital Entries and Exits: County-Level Analysis

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

	All		GOV		NP		FP	
Dep Variables:	(1) Entries	(2) Exits	(3) Entries	(4) Exits	(5) Entries	(6) Exits	(7) Entries	(8) Exits
Imm. Inflow (%)	-0.785	1.315***	0.360	-0.057	-0.444	1.405**	-0.524	0.145
	(0.582)	(0.272)	(0.223)	(0.142)	(0.415)	(0.610)	(0.447)	(0.204)
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

The table shows 2SLS regressions of the county-level hospital outcomes on instrumented immigration flows, similar to those in Table 5, Panel B. The changes in the number of hospitals are decomposed into *Entries* and *Exits*. In columns (1) and (2), *Entries* (*Exits*) are the number 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 (8), 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*. 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%.

Table A.3: OLS Regressions of Hospital Capacity: County-Level Analysis

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	
Dep Variables:	(1) Entries	(2) Exits	(3) Entries	(4) Exits	(5) Entries	(6) Exits	(7) Entries	(8) 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

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%.

Table A.4: The Effects of Immigration on Hospital Admissions: County-Level Analysis

	(1)	(2)	(3)	(4)	(5)
Dep. Variables:	ΔAdm. / Adm. (%)	ΔGOV Adm. / Adm. (%)	ΔNP Adm. / Adm. (%)	ΔFP Adm. / Adm. (%)	ΔPriv. Adm. / Adm. (%)
Imm. Inflow (%)	-2.520***	0.174	-2.694***	-0.001	-2.694***
	(0.499)	(0.273)	(0.434)	(0.379)	(0.542)
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	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}

The table shows 2SLS 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%.

Table A.5: The Effects of Insured and Uninsured Immigration Inflows: County-Level Analysis

	Mean	P10	P50	P90	SD	N
Panel A: Summary statistics with unweighted county observations						
Imm. inflow (insured) (%)	2.65	0.56	2.10	5.32	2.18	1,625
Pred. imm inflow insured (%)	2.37	0.59	1.56	4.91	2.40	1,625
Imm. inflow (uninsured) (%)	0.86	0.05	0.60	2.05	0.91	1,625
Pred. imm inflow uninsured (%)	0.72	0.13	0.43	1.70	0.76	1,625
Panel B: Summary statistics with county observations weighted by beginning-of-period population						
Imm. inflow (insured) (%)	3.83	1.19	3.30	7.40	2.41	1,625
Pred. imm inflow insured (%)	3.96	1.02	2.97	7.92	3.16	1,625
Imm. inflow (uninsured) (%)	1.20	0.26	0.92	2.74	1.01	1,625
Pred. imm inflow uninsured (%)	1.29	0.24	0.98	2.95	1.05	1,625

Panel C: Regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variables:	Imm. inflow (insured) (%)	Imm. inflow (uninsured) (%)	ΔBeds / Beds (%)	ΔGOV Beds / Beds (%)	ΔNP Beds / Beds (%)	ΔFP Beds / Beds (%)	ΔPrivate Beds / Beds (%)
Imm. inflow (insured) (%)			-0.962	0.232	-1.309*	0.115	-1.194
			(1.340)	(0.712)	(0.748)	(0.471)	(0.904)
Imm. inflow (uninsured) (%)			-6.825*	0.269	-5.507**	-1.587	-7.094*
			(4.017)	(2.242)	(2.796)	(2.920)	(3.917)
Pred. imm inflow (insured) (%)	0.980***	-0.015					
	(0.088)	(0.055)					
Pred. imm inflow (uninsured) (%)	-1.102***	0.686***					
	(0.322)	(0.234)					
Observations	1,625	1,625	1,625	1,625	1,625	1,625	1,625
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. Stage	1st	1st	2nd	2nd	2nd	2nd	2nd
F test (joint)	234.9	12.10					

The table reports results from the main county-level tests using immigration inflows decomposed into insured and uninsured. As in the main tests, total immigration inflow into a county *c* from *t-10* to *t*, $M_{c,t}$, is the number of foreign-born people living in county *c* in year *t* who have not been living in the U.S in year *t-10,* in percent of the county's population in *t-10*. This total inflow is decomposed into insured and uninsured, $M_{c,t}^I$ and $M_{c,t}^U$, based on a person's insurance status in year *t*. Thus, some individuals classified as insured at the end of the measurement period might have been uninsured earlier during that period. To construct instruments, we decompose the national inflows into insured and uninsured, where $R_{f,t}^I$ and $R_{f,t}^U$, denote inflows of insured and uninsured immigrants from country *f*. Using the same historical enclave shares as in the baseline specification, we construct the predicted insured and uninsured inflows, $Z_{c,t}^I$ and $Z_{c,t}^U$, which serve as instruments for $M_{c,t}^I$ and $M_{c,t}^U$.We then estimate a specification with two first stages and a combined second stage that includes both components of immigration, analogous to the main regressions in Table 4 (first column) and Table 5. Descriptive statistics are in Panels A and B. Regression results are in Panel C. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Table A.6: The Effects of Immigration on Nonprofit Hospital Donations and Contributions

	(1)	(2)
Dep. Variables:	ΔDonation (%)	ΔContribution (%)
Imm. Inflow (%)	-0.027	0.026
	(0.034)	(0.044)
Observations	1,385	1,271
State-year FE	Yes	Yes
County-type FE	Yes	Yes
Sample	NP Hosp	NP Hosp (IRS 990)
Reg. Stage	2nd	2nd

The table shows 2SLS 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 8, 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%.

Table A.7: Nonprofit Hospital Investment and Financing by Hospital Size and System Affiliation

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 (%)	-0.390	-1.223	-0.296	0.688	-0.272	-0.421	-0.533**
	(1.336)	(1.693)	(1.096)	(2.420)	(2.162)	(0.571)	(0.271)
Observations	2,796	2,723	2,908	2,322	2,565	2,143	2,796
			Unaffiliated Hospitals				
Imm. Inflow (%)	0.220	-0.920	1.409	-3.226	2.858*	0.563	-0.114
	(1.111)	(1.733)	(0.920)	(4.633)	(1.507)	(0.739)	(0.170)
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 (%)	-1.732	-2.366	-0.301	-1.921	-0.781	0.011	-0.508**
	(1.162)	(1.732)	(0.786)	(2.143)	(1.703)	(0.584)	(0.213)
Observations	2,372	2,316	2,424	2,203	2,257	2,114	2,371
			Small Hospitals				
Imm. Inflow (%)	0.058	-1.278	1.176	-0.500	2.540	-0.572	-0.307
	(1.315)	(2.320)	(0.914)	(4.241)	(2.509)	(0.653)	(0.249)
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

The table shows 2SLS regressions of hospital investment and financing measures on instrumented immigration flows, analogous to those in Table 10. 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%.

Table A.8: Descriptive Statistics for Hospital-Years Split Based on County's Population

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	

The table presents a comparison of subsamples of the hospital-years used in Table 3 (or Table 8, 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%.

Table A.9: Decomposing Uncompensated Care into Charity Care and Bad Debt

Panel A: Descriptive statistics

	Mean	P10	P50	P90	SD	N
Uncompensated (%)	6.89	1.87	5.47	12.62	6.26	5,100
Bad Debt (%)	4.98	1.15	3.83	9.58	4.95	4,757
Charity Care (%)	2.14	0.18	1.19	4.62	3.79	4,780
ΔUncompensated (%)	0.63	-4.77	0.22	6.21	4.84	5,100
ΔBad Debt (%)	0.41	-3.92	0.22	5.00	4.37	4,757
ΔCharity Care (%)	0.02	-2.13	-0.13	2.59	2.28	4,780

Panel B: Uncompensated care, bad debt, and charity regressions by organizational form

Sample:	GOV			NP			FP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Variables:	ΔUncompen-sated (%)	ΔBad Debt (%)	ΔCharity Care (%)	ΔUncompen-sated (%)	ΔBad Debt (%)	ΔCharity Care (%)	ΔUncompen-sated (%)	ΔBad Debt (%)	ΔCharity Care (%)
Imm. inflow (%)	2.046***	1.537***	0.483*	0.303**	0.227	0.160**	0.341	0.241	0.082
	(0.595)	(0.474)	(0.289)	(0.141)	(0.148)	(0.074)	(0.245)	(0.290)	(0.159)
Observations	487	450	458	3,425	3,294	3,306	1,188	1,013	1,016
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table presents 2SLS regressions of hospital-level uncompensated care and its components, charity care and bad debt, on instrumented immigration flows. Panel A shows descriptive statistics for the dependent variables. As in the main analysis, changes in uncompensated care and its components are computed over five-year periods *t-5* to *t* and are scaled by total revenues in *t-5*. The levels of uncompensated care and its components are as of *t-5* and are scaled by total revenues in *t-5*. Panel B shows results from second-stage regressions analogous to those reported in Table 8, Panel E. All regressions examine five-year measurement periods. 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%

Table A.10: Robustness Tests: Excluding Large Migrant Groups

Excluded Groups:	Mexicans		Chinese		Indians	
Dep. Variables:	Imm. Inflow (%) (1)	ΔNP Beds / Beds (%) (2)	Imm. Inflow (%) (3)	ΔNP Beds / Beds (%) (4)	Imm. Inflow (%) (5)	ΔNP Beds / Beds (%) (6)
Imm. Inflow (%)		-1.745***		-2.324***		-2.618***
		(0.468)		(0.609)		(0.703)
Pred. Imm. Inflow (%)	0.701***		0.671***		0.623***	
	(0.040)		(0.046)		(0.064)	
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	314		213.9		95.29	

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%.

Table A.11: Robustness Tests: Unweighted Regressions, Alternative Base Year, and Treatment of Foreign-Born Domestic Migrants

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 (%)		-1.266**		-3.164***		-3.401***
		(0.638)		(1.023)		(1.246)
Pred. Imm. Inflow (%)	0.742***		0.378***		0.370***	
	(0.045)		(0.088)		(0.076)	
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	1^{st}	2^{nd}	1^{st}	2^{nd}	1st	2nd
F test model	269.9		18.51		23.77	

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-10*); 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 who have been living in the U.S. prior to migrating into the county during *t-10* and *t* and subtracts foreign-born people who moved out of the county between *t-10* and *t*. In the main analysis, only recent immigrants – those who 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* in columns (3)-(6). Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Table A.12: Robustness Tests: Individual Ten-Year Windows

Dep. Variable:	ΔNP Beds / Beds (%)				
Sample:	2005-2015	2006-2016	2007-2017	2008-2018	2009-2019
	(1)	(2)	(3)	(4)	(5)
Imm. Inflow (%)	-2.510***	-2.401***	-2.045***	-1.616**	-2.287***
	(0.620)	(0.608)	(0.665)	(0.794)	(0.728)
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	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}

The table shows 2SLS 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%.

Table A.13: Robustness Tests: Five-Year Windows

	(1)	(2)	(3)	(4)	(5)
Dep. Variables:	ΔBeds / Beds (%)	ΔGOV Beds / Beds (%)	ΔNP Beds / Beds (%)	ΔFP Beds / Beds (%)	ΔPrivate Beds / Beds (%)
Imm. Inflow (%)	-2.491**	0.235	-2.367***	-0.360	-2.727***
	(0.977)	(0.393)	(0.515)	(0.578)	(0.909)
Observations	3,252	3,252	3,252	3,252	3,252
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Reg. Stage	2^{nd}	2^{nd}	2^{nd}	2^{nd}	2^{nd}

The table shows 2SLS 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-5. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Table A.14: Robustness Tests: MSA-level Analysis

Dep. Variables:	(1) ΔBeds / Beds (%)	(2) ΔGOV Beds / Beds (%)	(3) ΔNP Beds / Beds (%)	(4) ΔFP Beds / Beds (%)	(5) ΔPrivate Beds / Beds (%)
Imm. Inflow (%)	-1.751**	0.192	-1.296**	-0.647**	-1.943***
	(0.683)	(0.479)	(0.511)	(0.321)	(0.644)
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

The table shows 2SLS 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 243.59. Control variables include log(Population), 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%.

Table A.15: **Robustness Tests: Excluding Veterans' and Military Hospitals**

Dep. Variables:	(1) ΔBeds / Beds (%)	(2) ΔGOV Beds / Beds (%)	(3) ΔNP Beds / Beds (%)	(4) ΔFP Beds / Beds (%)	(5) ΔPrivate Beds / Beds (%)
Imm. Inflow (%)	-2.104**	0.284	-2.159***	-0.228	-2.388**
	(1.022)	(0.379)	(0.552)	(0.544)	(0.937)
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

The table shows 2SLS regression results, analogous to those in Table 5, Panel A, after excluding veterans' and military-affiliated hospitals from the sample. 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%.

Table A.16: Robustness Tests: Alternative Instrument

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**	0.215	0.024
			(0.382)	(0.264)	(0.279)
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	0.662	0.00743

Panel B: Estimating the effects of immigration using the IIG instrument unscaled

Dep. Variables:	(1) Imm. Inflow (000)	(2) ΔBeds	(3) ΔGOV Beds	(4) ΔNP Beds	(5) ΔFP Beds	(6) ΔPrivate Beds
Imm. Inflow (000)		-1.383***	0.797**	-1.244***	-0.936*	-2.180***
		(0.474)	(0.381)	(0.403)	(0.490)	(0.554)
IIG Instrument (000)	4.583***					
	(0.281)					
Observations	368	368	368	368	368	368
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
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	265.3					

Table A.16: Robustness Tests: Alternative Instrument, cont.

Panel C: Estimating the effects of immigration using the standard enclave instrument unscaled

Dep. Variables:	(1) Imm. Inflow (000)	(2) ΔBeds	(3) ΔGOV Beds	(4) ΔNP Beds	(5) ΔFP Beds	(6) ΔPrivate Beds
Imm. Inflow (000)		-2.721**	0.729	-2.400**	-1.050**	-3.450***
		(1.070)	(0.452)	(1.108)	(0.434)	(0.936)
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	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	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	131.4					

The table presents first-stage and second-stage regressions using Burchardi et al.'s (2019, 2026) 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. (2026) 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 (2026) 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. (2026) (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. 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 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. (2026), 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. Note that Imm. Inflow in Panel A refers to immigration inflows from Burchardi et al.'s (2026) data, while Imm. Inflow in Panels B and C refers to immigration inflows we obtained based on the Census data. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered at the MSA level. Significant at: *10%, **5% and ***1%.

Table A.17: Robustness Tests: Standard Errors

Dep. Variables:	(1) ΔBeds / Beds (%)	(2) ΔGOV Beds / Beds (%)	(3) ΔNP Beds / Beds (%)	(4) ΔFP Beds / Beds (%)	(5) ΔPrivate Beds / Beds (%)
Panel A: Main results with AKM exposure-robust standard errors					
Imm. Inflow (%)	-2.160***	0.240	-2.166***	-0.233	-2.399***
	(0.512)	(0.328)	(0.365)	(0.214)	(0.467)
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
Weight	Pop	Pop	Pop	Pop	Pop
Panel B: Main results scaling by county population in 2005; SEs clustered at the MSA level					
Imm. inflow 10y	-2.006**	0.265	-2.055***	-0.216	-2.272***
(% of 2005 pop)	(0.946)	(0.351)	(0.525)	(0.527)	(0.879)
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
Weight	Pop 2005	Pop 2005	Pop 2005	Pop 2005	Pop 2005
Panel C: Main results scaling by county population in 2005; BHJ SEs clustered by origin country					
Imm. inflow 10y	-2.007**	0.266	-2.056***	-0.217	-2.272***
(% of 2005 pop)	(0.783)	(0.244)	(0.623)	(0.192)	(0.771)
Observations	565	565	565	565	565
State-year FE	Yes	Yes	Yes	Yes	Yes
County-type FE	Yes	Yes	Yes	Yes	Yes
Weight	Pop 2005	Pop 2005	Pop 2005	Pop 2005	Pop 2005

The table presents second-stage regressions similar to those in Table 5, Panel A, using inference procedures that account for the shift-share structure of the instrument. In all three panels, 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 A, the specification is identical to Table 5, but standard errors follow Adão, Kolesár, and Morales (2019): the AKM sandwich formula accounts for cross-county correlation induced by common origin-country shocks, replacing the MSA-level clustering used in Table 5. In Panel B, the treatment and instrument are rescaled by each county's 2005 population rather than the time-varying population, and observations are weighted by 2005 county population; standard errors are clustered at the MSA level as in Table 5. Panel B thus replicates Table 5 Panel A under the 2005-population normalization, providing a county-level benchmark for Panel C. In Panel C, the data are collapsed to the origin-country × year (shock) level following Borusyak, Hull, and Jaravel (2022), with the same 2005-population normalization as in Panel B; standard errors are clustered by origin country. The coefficient in Panel C should be interpreted alongside Panel B: any difference from Table 5 reflects the change in normalization, not the shift to shock-level estimation. The number of observations in Panel C is 565, corresponding to the number of foreign countries in each of the five 10-year windows. We identify 133 birthplaces from 2000 onward, including U.S. and "Others." Foreign birthplaces with fewer than 10,000 individuals or other ambiguous cases are grouped as "Others." Of the 132 foreign birthplaces, 18 are not present in 2000, reducing the number of foreign birthplaces to 114=(132-18). Of those, 112 appear in all five windows (112 x 5=560), one in only the last three, and another in only the first two, totaling 565 windows. All specifications include state × year fixed effects, county-type fixed effects, and the same controls as Table 5. Variable definitions are in Appendix A. Significant at: *10%, **5% and ***1%.

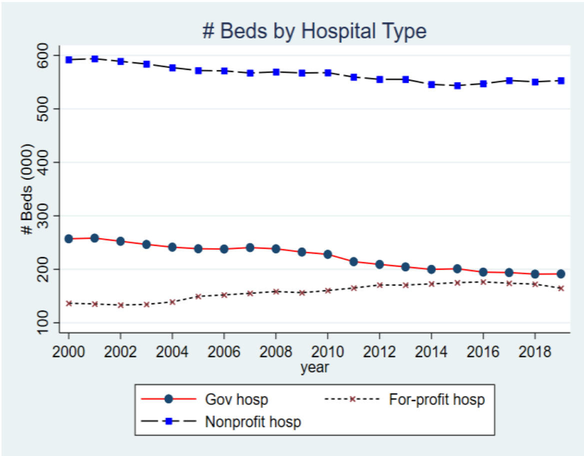
Online Appendix Figures

Figure A.1

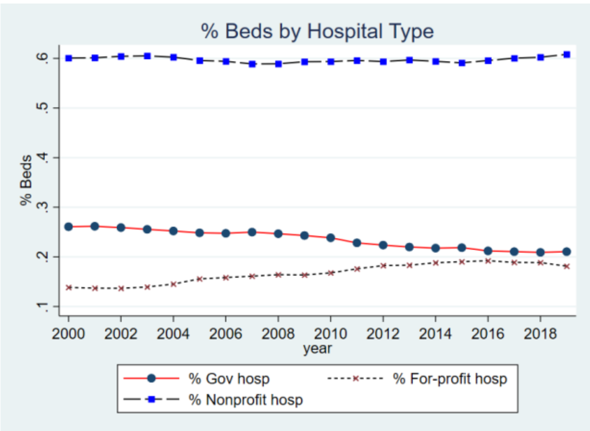
Hospital Beds over Time by Organizational Form

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



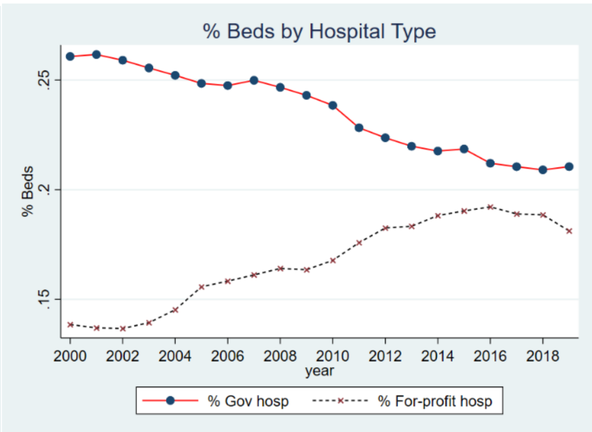


Figure A.2

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.

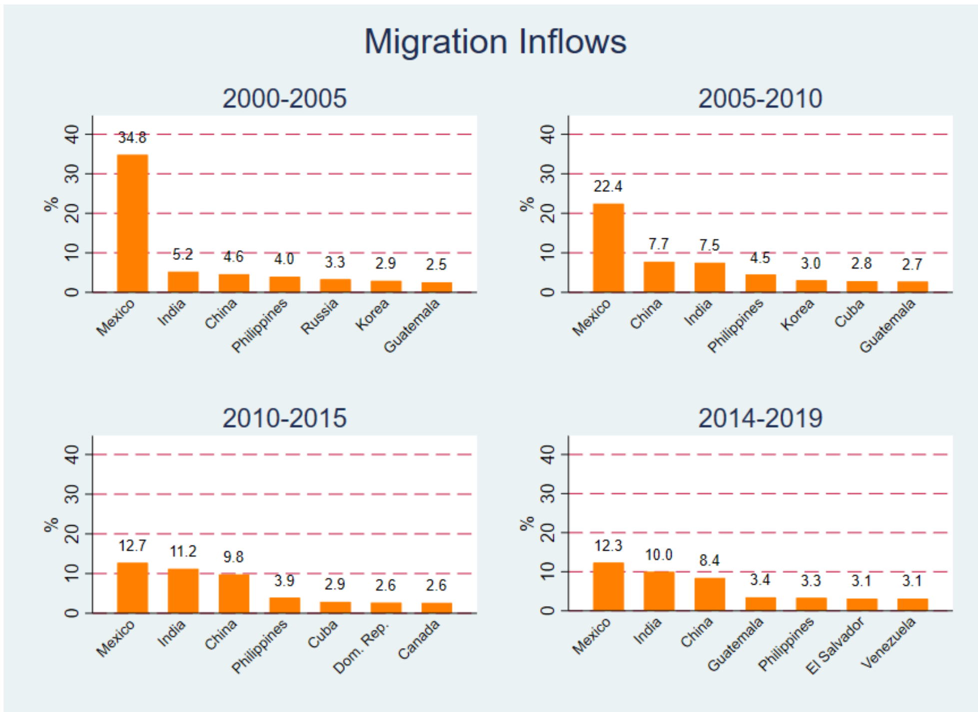
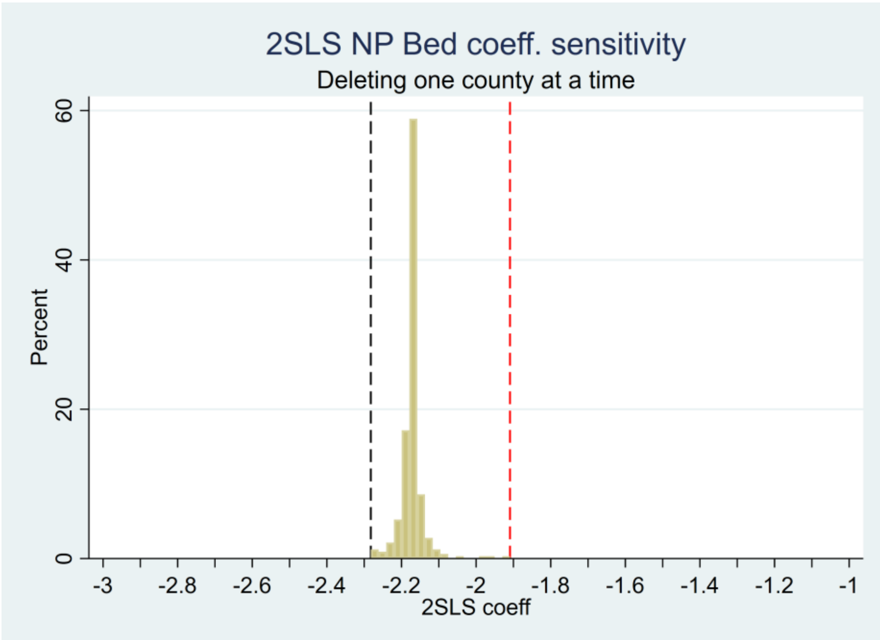


Figure A.3

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 4, 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