Immigration, Innovation, and Growth*

Stephen J. Terry ⓡ[†]   Thomas Chaney ⓡ[‡]

Konrad B. Burchardi ⓡ[§]   Lisa Tarquinio ⓡ[¶]   Tarek A. Hassan ⓡ[‖]

February 2024

Abstract

We propose a novel identification strategy to isolate exogenous immigration shocks across US counties, by interacting quasi-random variations in the composition of ancestry across counties with the contemporaneous inflow of migrants from different countries. We show a positive causal impact of immigration on local innovation and wages at the 5-year horizon. The positive dynamic impact of immigration on innovation and wages dominates the short-run negative impact of increased labor supply. A structural estimation of a model of endogenous growth and migrations suggests the increased immigration to the US since 1965 may have increased innovation and wages by 5%.

JEL Classification: J61, O31, O40.

Keywords: migrations, innovation, patents, endogenous growth, dynamism.

---

*The random order ⓡ reflects the equal contribution of all authors. We are grateful to Ran Abramitzky, Daron Acemoglu, David Autor, David Atkin, Murat Celik, William Kerr, Klaus Desmet, Ray Fisman, Lisa Kahn, Kevin Lang, Ethan Lewis, Ömer Özak, Michael Peters, Chris Tonetti, Pascual Restrepo, and numerous seminar participants for helpful comments. We thank Giao Dang for her excellent research assistance. Chaney is grateful for financial support from ERC grants N°337272 and N°884847. All remaining mistakes are our own. This paper is dedicated to the memory of Dr. Sherif A. Hassan.

[†]University of Michigan and NBER, 611 Tappan Avenue, Ann Arbor, MI 48104, USA; E-mail: sjterry@umich.edu.

[‡]University of Southern California, Sciences Po, and CEPR; E-mail: thomas.chaney@gmail.com.

[§]Institute for International Economic Studies, 106 91 Stockholm, Sweden; E-mail: konrad.burchardi@iies.su.se.

[¶]University of Western Ontario, 1151 Richmond Street, London ON N6A 5C2, CA; E-mail: ltarqui@uwo.ca.

[‖]Boston University, NBER and CEPR, 270 Bay State Road, Boston MA 02215, USA; E-mail: thassan@bu.edu.

Does immigration cause more or less innovation and growth? In this paper, we answer this question in the context of international migration to the US over the last four decades. We find a positive causal impact of immigration on innovation and wage growth at the local level (US counties) over a short horizon (five-year periods) and interpret these findings through the lens of a model of endogenous growth and migrations.

Canonical theories of economic growth suggest a role for immigrants in driving local economic outcomes. Immigrants bring ideas, skills, and effort, and increase demand for new inventions, which stimulates growth (Romer, 1990; Jones, 1995). In the presence of frictions on mobility, trade, or idea flows, regional models suggest immigrants should have local, not just aggregate, effects on innovation and wages (Desmet et al., 2018; Peters, 2022). In contrast to these predictions, fierce political controversies surround the economic contribution of migrants: do migrants drain resources from their host communities and stifle innovation?

A rigorous quantification of the causal impact of immigration on innovation and growth has often proven elusive. The reason is that migrants do not allocate randomly across space. Instead, they are likely to choose innovative destinations that offer the best prospects for them, creating a spurious correlation between immigration, innovation, and economic growth.

We make three main contributions to the literature on immigration and growth. First, we propose a formal identification strategy to estimate the causal impact of migrations on innovation and wage growth. We build upon the seminal work of Card (2001) but add one key innovation: instead of using the realized pre-existing distribution of foreign origins to predict new migrations, we construct a granular set of instruments for this pre-existing distribution, using 130 years of country-county-level migration data. Second, we show that immigration causes a large and persistent increase in local innovations and in the wages earned by natives. Immigration also has distributional effects: more educated natives benefit more from it, and more educated migrants have a stronger positive impact on local wages and innovations. Third, we combine this credibly identified evidence with a regional model of innovation and migrations to structurally estimate the local elasticity of innovation to research labor. This elasticity determines the size of local scale effects and the aggregate response to large-scale immigration.

Our structural model also helps reconcile the seemingly contradictory evidence on the impact of immigration on native wages (Card, 1990; Borjas, 2003): immigration, a labor supply shock, exerts a negative neo-classical downward pressure on wage; but it also induces dynamic innovations and wage growth. For the US, on average over the last 40 years, the positive impact from innovation dominates the negative impact from increased labor supply.

We now turn to a description of our three main contributions.

Our first contribution is a granular identification strategy able to isolate quasi-random immigration shocks for each US county in each five-year period starting in 1975. As in the canonical shift-share approach, we rely on the tendency of newly arriving migrants to settle in US counties with large pre-existing communities of the same origin. But instead of using past realized immigration (Card, 2001) or ancestry (Tabellini, 2019) to measure the pre-existing distribution of foreign origins, we instrument for the pre-existing ancestry distribution (Burchardi et al., 2019). Doing so, we guard against the concern that where migrants choose to settle within the US, both in recent decades (the distribution of immigrants) and in the more distant past (the distribution of ancestry), may be correlated with persistent productivity shocks and other unobserved factors that also affect local innovation and growth.[1]

To isolate quasi random immigration shocks, we proceed in two steps. In a first step, we follow the method in Burchardi et al. (2019) to construct a set of instruments for the pre-existing distribution of foreign ancestry in 1975. For each period starting in 1880, we predict the number of migrants from a given origin country to a given destination county by interacting the total number of migrants arriving in the US from that country with the share of foreign migrants from other origins who settle in that US county. Iterating this procedure over 100 years, we isolate quasi-random variation in the distribution of ancestry across counties in 1975.

In a second step, we follow the canonical shift-share approach: for each period starting in 1975, we estimate migration into a county from a foreign origin country using only the interaction of *predicted* pre-existing ancestry and the contemporaneous inflow of migrants from that origin. Summing over all origin countries, we predict the total number of migrants flowing into each US county at each point in time post 1975 (our panel of immigration shocks).

To further guard against any lingering concerns about identification, we estimate the impact of immigration shocks on *changes* in local innovation and growth, not levels. In many specifications, we even include county fixed effects to control for county-specific trends.

Our second contribution is to quantify the causal impact of immigration on innovation and growth in reduced form. We find a positive and significant causal impact of local immigration on the growth in local patents filed per person: on average, the arrival of 10,000 additional

[1] David Card himself notes that past immigration shares may be endogenous (Card, 2001, p. 43), and a large literature has since highlighted inference and consistency issues arising from this core issue (e.g. Adão et al., 2019; Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018). David Card further states "[o]ne could potentially overcome this problem by finding a set of instruments that explain the location choices of earlier immigrants from different source countries and using predicted settlement patterns of the earlier cohort to construct the supply push indexes." This is precisely the task we undertake in this paper.

immigrants in a county (close to one standard deviation) increases growth in the flow of patents over a five-year period by 1.22 patents per 100,000 residents, an increase of 25% relative to its mean (4.61 new patents per 100,000 residents). Immigration also causes a significant increase in local real income growth. 10,000 additional adult immigrants increase wages per capita by $150 (in 2010 dollars), an 8% higher annual wage growth for local workers on average.

The positive effect of immigration on local wages is stronger for more educated native workers: for instance, the same immigration shock increases the wages of college graduates five times more than those of high school graduates. More educated migrants also have a stronger positive impact on local innovation and wage growth: for instance, the increase in the flow of patents caused by immigration is five times larger for migrants with one standard deviation higher education (3.7 more years of schooling) than for migrants of average education (11 years of schooling). We also show that the positive effect of immigration on innovation comes primarily from increased patenting by domestic inventors (about 80%), and to a smaller extent from immigrant inventors and mixed teams of domestic and immigrant inventors. Finally, we find evidence that the positive effect of immigration on innovation and wage growth diffuses over space, with surrounding counties within 100km (60 miles) also benefiting significantly.

Our third contribution is to construct a structural model of endogenous growth and migrations. We use this model to estimate the elasticity of local innovation to research labor, to quantify the aggregate impact of immigration on innovation and growth, and to illustrate the challenges to reduced-form identification. Migrants endogenously choose where to settle within the US, preferring destinations with higher expected wages and larger communities of their same origin. Workers in local labor markets innovate and produce goods. An immigration shock, a positive labor supply shock, decreases local labor cost, but also stimulates local innovation and productivity growth, making workers more productive. Over a five-year period, the innovation channel dominates so that local wages increase by a small amount initially; over time these positive effects build up, leading to a persistent increase in local wages and innovation. We structurally estimate our model, targeting the well-identified reduced form effect of immigration on local innovation. We estimate an elasticity of local research output with respect to local research labor equal to 0.8. In addition to governing the distribution of idea production across regions, this elasticity disciplines the magnitude of the aggregate response to immigration shocks. To illustrate this response, we conduct a counterfactual experiment, removing the large rise in immigration to the US after the 1965 Immigration National Act (a counterfactual reduction of approximately 1/6 of total population growth). This exercise suggests that without the increased immigration between 1965 and 2010, US per capita patenting and income would be around 5% below their current steady state level.

We also show that within our model of endogenous migrations, the identification restriction for a simple shift-share instrument for immigration as in Card (2001) and the subsequent literature are violated: a positive productivity shock increases wages and attracts migrants; because local productivity shocks are highly persistent, the pre-existing distribution of foreign origins correlates with contemporaneous productivity shocks for long periods of time. In contrast, within our model, our identification strategy generates instruments that are orthogonal to such shocks and also guard against more subtle, county-country specific, confounds to identification.

Related Literature. Our paper bridges four strands of the literature.

First, many studies use variants of the canonical shift-share instrument (Card, 2001) that takes pre-existing foreign-origin shares as given. Recent micro-econometrics advances have clarified the conditions under which shift-share designs are valid (Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020), and why they lead to over-rejection rates (Adão et al., 2019). We build on this literature and isolate exogenous variation in the pre-existing spatial distribution of ancestry to construct plausibly exogenous immigration shocks to US counties not subject to these concerns. We also explain, within the controlled environment of a structural model linking local innovation to persistent productivity shocks and endogenous migrations, why conventional shift-share designs are likely biased, while our identification strategy is not.

Second, we contribute to a large empirical literature on the link between immigration, innovation, and technology adoption. This literature has documented large contributions of high-skilled immigrants to innovation and dynamism in the US (Kerr and Lincoln, 2010; Hunt and Gauthier-Loiselle, 2010; Stuen et al., 2012; Akcigit et al., 2017; Arkolakis et al., 2020; Khanna and Lee, 2018), spillovers from the arrival of high-skilled scientists and inventors on the productivity of their American peers (Borjas and Doran, 2012; Moser et al., 2014; Bernstein et al., 2018; Moser et al., 2021), and the contribution of migrants to the diffusion of knowledge across borders, local technology adoption, and output and employment (Kerr, 2008; Lewis, 2011; Lafortune et al., 2019; Tabellini, 2019; Sequeira et al., 2020).[2] Our results confirm the disproportionate positive impact of high-skilled migrants on innovation, but also show that the positive impact of immigration is primarily driven by domestic innovators.

Third, we contribute to the labor literature on immigration and local labor markets (Borjas,

[2] Hanson (2009, 2010) and Lewis (2013) provide early surveys. Lewis and Peri (2015) and Abramitzky and Boustan (2017) give an overview of the broader literature on the effect of immigration on regional economies.

2003; Cortes, 2008; Ottaviano and Peri, 2012; Foged and Peri, 2016; Dustmann et al., 2017; Monras, 2020; Jaeger et al., 2018; Bratsberg et al., 2019). We show that immigration has a nil impact on the wages of the least educated native workers at the 5-year horizon, but a strong positive impact for more educated workers. More educated migrants also have a stronger positive impact on native wages.[3] Moreover, our structural model suggests these effects are time-varying: immigration increases labor supply which exerts downward pressure on wages on impact; but it also fosters innovation, which increases labor productivity and wages over time. This heterogeneity across groups and over time may explain the seemingly contradictory results the empirical literature has documented in different settings. We show that for the US over the last 40 years, the average local effect of immigration on wages is positive.

Fourth, endogenous growth theory predicts a positive impact of population growth on economic growth and innovation (Romer, 1990), with the nature of these scale effects depending upon the technology for producing ideas and the horizon of analysis (Jones, 1995, 1999; Peretto, 1998; Young, 1998; Laincz and Peretto, 2006; Bloom et al., 2020). The local effects of immigration across models depends on frictions to mobility, trade, and idea diffusion (Desmet et al., 2018; Peters, 2022; Monte et al., 2018; Giannone, 2019; Arkolakis et al., 2020). The quantitative predictions of these models crucially rely on the local scale effect in innovation. Instead of disciplining this object by matching moments of income growth, the usual approach, we structurally estimate its value using our empirical estimates of the link between immigration and innovation. Our counterfactual exercise also shows that local scale effects in innovation govern the aggregate response to immigration, and contributes to a growing literature focused on the interpretation of regional evidence (Nakamura and Steinsson, 2014; Guren et al., 2021).

The paper is structured as follows. Section 1 introduces our data. Section 2 lays out our identification strategy. Section 3 estimates the causal effect of immigration on innovation and wage growth. Section 4 structurally estimates a model of endogenous innovation and migrations.

1 Data

We collect detailed data on migration, ancestry, migrants' education, patents, and local labor markets. Throughout the paper, we use the subscripts o for origin country, d for US destination county, t for the end year of a 5-year interval, and $t-1$ for the end year of the previous 5-year interval. Summary statistics are in Table 1 and further details are in Appendix A.

[3] Arkolakis et al. (2020) estimate the heterogeneous contribution of European immigrants of different skills on US innovation 1880-1920. We document similar patterns for recent decades.

Immigration and Ancestry. Following Burchardi et al. (2019), our immigration and ancestry data are constructed from the individual files of the Integrated Public Use Microdata Series (IPUMS) samples of the 1880, 1900, 1910, 1920, 1930, 1970, 1980, 1990, and 2000 waves of the US census, and the 2006-2010 five-year sample of the American Community Survey. We weigh observations using the personal weights provided by these data sources. I_{odt} is the number of respondents who immigrated from o to d between $t-1$ and t. A_{odt} is the number of respondents in d who claim ancestry from o at t. Our dyadic dataset covers 3,141 US counties, 195 foreign countries, and 10 census waves. Appendix A.1 gives additional details.

Innovation. To measure innovation we use patent microdata from the US Patent and Trademark Office (USPTO) from 1975 until 2010. We match the patent assignee locations from the USPTO in coordinate form to 1990 US counties, tabulating the number of corporate utility patents granted to assignees in each county in each year of the sample.[4] The patent flow in county d at t is the sum of patents filed in the 5-year period ending at t. We normalize this variable by the 1970 county population to measure patent flow per capita. Our primary outcome of interest is the *change* in patent flows per capita between the 5-year period ending in t and the 5-year period ending in $t-1$. Appendices A.2 and A.3 give additional details.

Wages. We compute from 1975 to 2010 the local average annual wages using the Quarterly Census of Wages (QCEW) dataset from the US Bureau of Labor Statistics, deflated by the Personal Consumption Expenditure price index. Our primary outcome of interest is the change in real wages per capita over 5 years (measured in 2010 dollars). We also compute the change in the average annual wages over 10 years, CPI-deflated, for US-born workers (natives) and the subset of natives who have lived in the same county for five years (native non-movers) using data from IPUMS USA. Appendix A.4 gives additional details.

2 Constructing a Valid Instrument for Immigration

Our aim is to estimate the causal impact of immigration on innovation and local wage growth, which can inform a structural model of endogenous growth and migrations. We estimate

$$\Delta Y_{d,t} = \delta_t + \delta_{s(d)} + \beta \cdot \text{Immigration}_{d,t} + \epsilon_{d,t}, \tag{1}$$

where $\text{Immigration}_{d,t}$ measures the number of migrants flowing into destination county d between $t-1$ and t. $\Delta Y_{d,t}$ is a change from $t-1$ to t in the outcome of interest, usually the

[4] We use the location of assignees rather than innovators as the majority of recent patents are assigned to corporations, unlike in earlier periods (Akcigit et al., 2017). For robustness, we also replicate our results using alternative assignments, and various weights to control for patent quality (Hall et al., 2001).

change in the number of patents filed per capita in the county. This specification in *changes* ensures any long-lasting differences between counties that are on average more or less innovative are controlled for, and eliminates the skewness of the left hand side variable. δ_t and $\delta_{s(d)}$ are time and state fixed effects, respectively. Our most conservative specifications also include a county fixed effect, δ_d, which controls for any county-specific trend in $Y_{d,t}$, so that for example we exploit only deviations from the county's average growth of patent flows over time.

The main concern with a simple OLS estimate of β is that unobserved factors may affect both immigration and innovation, even though we estimate (1) in differences, and even with fixed effects that absorb state- or county-specific trends. We spell out two identification concerns explicitly, and propose a solution. The first is a simple *reverse causality* concern: local wages are likely correlated with local productivity shocks and innovation, and foreign migrants are in part attracted by higher wages. This induces a spurious correlation between immigration and innovation, where counties that become more innovative attract more migrants over time because they pay higher wages. The second is a *county-country specific omitted factors* concern: workers from a specific country (say India) may disproportionately have specific skills (say engineering) well-suited for specific sectors (say telegraph, aeronautics, and software development) that are concentrated in a specific county (say Silicon Valley in Santa Clara county). Any time a positive shock to productivity and innovation occurs in that sector (e.g. a shock to the telegraph industry in the 1900's, to aeronautics in the 1960's, or to software development in the 2000's), workers from that country (India) will be drawn to this county (Silicon Valley) – resulting in spurious correlations between local innovation, immigration, and foreign ancestry.[5]

We propose an identification strategy plausibly immune to both concerns. Drawing on the seminal work of Card (2001), we leverage the tendency of incoming migrants to settle in US counties with large pre-existing communities from the same ancestry. However, we depart from Card (2001) and the subsequent literature employing the canonical shift-share approach by using only plausibly exogenous variation in pre-existing ancestry.

The identification strategy is best described by a stylized example. We predict a relatively large inflow of migrants from o (say Indians relative to other Asians) to d (say Fresno in the Central Valley of California relative to other destinations on the West Coast) at a point in history τ (say 1900) if the following happens: in 1900, many Indians migrate to the United States including towards regions outside the West Coast (1900 corresponds to the first historical

[5]A conventional shift-share design would wrongly assume that pre-existing immigration or ancestry shares (e.g. Indians engineers in Silicon Valley) are orthogonal to future innovation shocks (e.g. shocks to the tech sector in Silicon Valley).

Indian migration wave to the US) *and* Fresno county is attractive to foreign migrants from any origin, including from Europe (1900 corresponds to the beginning of oil exploitation in Fresno, and an increase in agricultural production following the construction of irrigation canals in the late 19th Century). This early settlement of Indian migrants in Fresno partly explains the large community of Indian ancestry in Fresno after 1975.[6] Our identification strategy applies this logic for all periods starting in 1880, all origin countries, and all destination counties. We isolate granular variation in the ancestry composition of US counties that emanates solely from the coincidence of migrants being 'pushed' from their country and 'pulled' into US counties attractive to the average migrant. We then simply apply the Card (2001) shift-share method using predicted ancestry: any time post-1975 there is a large inflow of migrants from India to the US, we predict Fresno receives a positive immigration shock, because some newly arriving Indian migrants choose to settle in Fresno with its large (exogenous) pre-existing Indian community.

Step 1: Predicting ancestry. To predict the number of residents with ancestry from o who reside in d at t, $A_{o,d,t}$, we apply the method developed in Burchardi et al. (2019). We only give a brief summary here. Burchardi et al. (2019) show that a simple reduced form model of migrations driven by 'push' and 'pull' shocks, combined with a rigorous leave-out strategy, allows to identify variations in $A_{o,d,t}$ that are plausibly exogenous not only to local factors, d-specific, but also to bilateral factors, (o, d)-specific. We develop a structural model of migrations explicitly featuring those two forces in Section 4. Formally, we estimate

$$A_{o,d,t} = \delta_{o,r(d)} + \delta_{c(o),d} + X'_{o,d}\zeta + \sum_{\tau=1880}^{t} a_{r(d),\tau} I_{o,-r(d),\tau} \frac{I_{Europe,d,\tau}}{I_{Europe,\cdot,\tau}} + \upsilon_{o,d,t}, \qquad (2)$$

where $I_{o,-r(d),\tau}$ is the total number of migrants arriving from o at τ who settle in counties *outside* of the region $r(d)$ where d is located,[7] a 'push from o' shock. $I_{Europe,d,\tau}/I_{Europe,\cdot,\tau}$ is the share of *European* migrants who settle in d at τ, a 'pull to d' shock. $\delta_{o,r(d)}$ and $\delta_{c(o),d}$ are a series of origin country × destination region and origin continent × destination county interacted fixed effects, and $X_{o,d}$ contains a series of time-invariant controls for $\{o, d\}$ characteristics. We estimate (2) separately for each $t = 1980, 1985, 1990, 1995, 2000, 2005, 2010$ using all non-European countries in our sample. From this estimation, we derive predicted ancestry

$$\hat{A}_{o,d,t} = \sum_{\tau=1880}^{t} \hat{a}_{r(d),\tau} \left(I_{o,-r(d),\tau} \frac{I_{Europe,d,\tau}}{I_{Europe,\cdot,\tau}} \right)^{\perp}, \qquad (3)$$

[6]Appendix Figure 1 shows how the timing of migrations varies between foreign origins; one can notice the early (small) spike in Indian migration in 1900. Appendix Figure 2 shows that US counties are attractive to foreign (European) migrants at different points in time; Fresno in 1900 was attractive to Europeans migrants.

[7]'Region' refers to the nine US census divisions, on average 5 adjacent states (see Appendix Table 1).

where $\hat{a}_{r(d),\tau}$ are the coefficients estimated from (2) and $\perp$ indicates that the interaction of push and pull factors has been residualized with respect to all of the controls in (2), isolating the variation in predicted ancestry exclusively attributable to these instruments.

This reduced form regression captures the intuition above: we expect a large community of ancestry from India living in Fresno in 1980 if many Indian migrants in 1900 settled outside the West Coast ($I_{India,-r(Fresno),1900}$ large) and Fresno in 1900 was attracting a large share of European migrants ($^{I_{Europe,Fresno,1900}}/_{I_{Europe,\cdot,1900}}$ large). Given both the 'push-pull' interaction and the restrictive leave-out strategy (we exclude the West Coast from India's push, and exclude all non-European migrants from Fresno's pull), we ensure that predicted ancestry from (2) does not suffer from the endogeneity concerns above. For instance, we leave-out Indian migrants with specific skills who may have endogenously chosen where to settle. Had we used realized ancestry instead, we may have included 1980 descendants of 1960 Indian migrants with engineering skills who endogenously settled in Silicon Valley at the time of the early development of aeronautics. This would have induced a spurious correlation between contemporaneous Indian ancestry and productivity and innovation shocks in Silicon Valley, such as software development in 2000.

Step 2: Predicting immigration. Having predicted pre-existing ancestry, we can now simply apply the canonical shift-share approach by interacting *predicted* pre-existing ancestry in a given county with contemporaneous (US-wide) immigration from that origin,

$$I_{o,d,t} = \delta_{o,r(d)} + \delta_{c(o),d} + \delta_t + X'_{o,d}\theta + b_t \cdot [\hat{A}_{o,d,t-1} \times \tilde{I}_{o,-r(d),t}] + u_{o,d,t}, \tag{4}$$

where again the δ's are time, country×region, and continent×county fixed effects, $X'_{o,d}$ observable controls, $\hat{A}^{t-1}_{o,d}$ predicted ancestry from (3), and $\tilde{I}_{o,-r(d),t} = I_{o,-r(d),t}\left(^{I_{Europe,r(d),t}}/_{I_{Europe,-r(d),t}}\right)$ the scaled push factor from o. (Because we leave out from $I_{o,-r(d),t}$ all migrants from o who settle in d's region, scaling by $^{I_{Europe,r(d),t}}/_{I_{Europe,-r(d),t}}$ corrects for differences in region sizes.)

Adding up across foreign origins, we derive our main instrument for the total number of migrants settling in county d in period t, $\text{Immigration}_{d,t}$ in (1),

$$\hat{I}_{\cdot,d,t} = \sum_o \hat{b}_t \cdot [\hat{A}_{o,d,t-1} \times \tilde{I}_{o,-r(d),t}]. \tag{5}$$

This instrument predicts a large immigration shock to Fresno county in 2000 if (i) many Indians migrate to the US in 2000 (excluding the West Coast), and (ii) we predict a large pre-existing community of Indian ancestry in Fresno. The key innovation relative to Card (2001) is to rely on predicted ancestry using historical migrations, instead of realized immigration or ancestry.

Identifying assumption. A sufficient condition for the validity of this instrument is that predicted ancestry, $\hat{A}_{o,d,t-1}$, is exogenous in equation (1). With our baseline regional and continental leave-outs, we can write this condition as

$$I_{o,-r(d),\tau}\frac{I_{Europe,d,\tau}}{I_{Europe,\cdot,\tau}} \perp \epsilon_{d,t} \forall o, \tau \leq t. \tag{6}$$

It requires that any confounding factors that drive temporary increases in a given US county's innovation post-1975 ($\epsilon_{d,t}$) do not systematically correlate with pre-1975 immigration from a given origin to other regions within the US ($I_{o,-r(d),\tau}$) interacted with the simultaneous settlement of European migrants in that US destination ($^{I_{Europe,d,\tau}}/_{I_{Europe,\tau}}$). If this condition is satisfied, the ancestry variable used to predict immigration in (5) is exogenous.[8]

Performance of the instrument. Table 2 shows the results from estimating various specifications of (4). The interaction of predicted ancestry ($\hat{A}_{o,d,t-1}$)[9] with national immigration shocks ($\tilde{I}_{o,-r(d),t}$) predicts immigration flows post-1975 ($I_{o,d,t}$) accurately: the R^2 in column 1 without any controls is 65.6%. Importantly, the coefficients on the interaction between predicted ancestry and national immigration are virtually unchanged as we add more controls: controlling for distance, latitude distance, country and county fixed effects in column 2; adding 14,031 country × census division and county × continent interacted fixed effects in column 3; controlling for the (endogenous) total flow of European migrants to the same county in column 4; and controlling for the push-pull interaction that shapes immigration in column 5. Appendix Figure 4 provides maps displaying these exogenous "immigration shocks" for each five-year period from 1975 to 2010, $\hat{I}_{\cdot,d,t}$ in (5), with substantial variation over time and space.

3 The Impact of Immigration on Innovation and Growth

In this section, we exploit our quasi-random immigration shocks to quantify the causal impact of immigration on innovation and growth, and probe the robustness of our results.

[8]Exogeneity of ancestry is a sufficient, but generally not a necessary condition for the validity of the shift-share approach (Goldsmith-Pinkham et al., 2020). See Borusyak, Hull, and Jaravel (2021) for necessary and sufficient conditions for the validity of the shift-share instrument of Card (2001) and Bartik (1991).

[9]Appendix Figure 3 shows a binned scatter plot of predicted ancestry ($\hat{A}_{o,d,2010}$) against actual ancestry ($A_{o,d,2010}$), well aligned along the 45-degree line.

3.1 Immigration and Innovation

Table 3 shows our main results, a test of the hypothesis that immigration *causes* an increase in innovation at the local level (US county), in the short run (five-year period). Our baseline estimate for coefficient β in (1) is in panel B column 1. It measures the impact of an exogenous inflow of immigrants to county d (in 1,000s) on the *change* in the number of patents per 100,000 residents filed over five years, where we instrument for immigration using our immigration shocks (5). The estimated effect is positive and statistically significant (0.122, s.e.=0.045). It implies that 10,000 additional immigrants to a county (close to one standard deviation, 12,000) increases the flow of patents filed locally over a five-year period by $0.122 \times 10 = 1.22$ patents per 100,000 people, from 4.61 patents (its mean) to 5.83, a 25% increase.

Panel A shows OLS estimates, panel B our IV estimates, and panel C estimates of the first stage of our IV. Across specifications, our IV estimates are lower than OLS estimates (though not statistically significantly different), suggesting that migrants endogenously sort into destinations that experience an increase in innovation.[10] Consistent with the presence of reverse causality or country-county specific confounding factors, the OLS estimates are unstable as we add more controls, state×time fixed effects in column 2, and county fixed effects in column 3. By contrast, the IV estimates remain stable across specifications, even when controlling for county fixed effects, so exploiting solely variation in the growth rate of innovation within-county over time. This stability bolsters our confidence that our exogenous immigration shocks are orthogonal to persistent confounding factors at the county-level. Our first stage has a strong F-statistic (always above 85) and Anderson-Rubin Wald F-test (all p-values below 2%).

Finally, column 4 shows an alternative functional form, the *elasticity* of innovation to immigration. Instead of estimating the impact of immigration on innovation in levels as in (1), we use the inverse hyperbolic sine transformation, IHS, which approximates the logarithm function,

$$IHS\left(Patents_{dt}\right) = \delta_t + \delta_{s(d)} + \beta_{IHS} IHS\left(Immigration_{dt}\right) + \epsilon_d^t, \tag{7}$$

where we instrument for immigration using the same instrument (5) as in our baseline specification. We find a large and significant elasticity of patenting to immigration shocks, $\beta = 1.652$ ($s.e. = 0.150$). We interpret this large positive impact of immigration on the flow of patenting through the lens of a regional endogenous growth model in Section 4, and we quantify this model targeting the well identified reduced form elasticity β_{IHS}.

[10] Note that the standard errors are lower in the IV specifications than in the OLS specification. This is because we compute cluster-robust standard errors (Cameron and Miller, 2015).

3.2 Immigration and Wage Growth

Table 4 tests the hypothesis that immigration *causes* an increase in local wages. Even if immigration has a positive impact on innovation as documented above, the impact on wages is theoretically ambiguous, as we show formally in Section 4. An inflow of immigrants increases the local supply of labor, which depresses wages. At the same time, it induces a rise in local innovation, which increases the marginal product of labor and pushes wages up. The net effect of immigration on local wages in the short run thus remains an empirical question.

We show that immigration has a positive impact on local wages over a 5-year horizon at the county level, controlling for state fixed effects (column 1) and county fixed effects (column 2).[11] An influx of 10,000 adult migrants (close to one standard deviation, 7,000) increases wages per capita by around 8% relative to the mean increase in our sample.[12] This is not mechanically driven by high-earning migrants, nor by a composition effect where low-earning natives may leave in response to the arrival of migrants (Borjas, 2003): immigration induces an increase in wages even when restricting our analysis to native non-movers (column 3).

3.3 Immigration and Wage Inequality

We next show that immigration shocks are intimately linked to the dynamics of wage inequality: an immigration shock has a stronger positive impact on more educated native workers; and more educated migrants contribute more to US innovation and wage growth.

High versus low education natives. Columns 4 to 8 in Table 4 estimate the impact of an exogenous immigration shock on the change in wages separately for native non-movers with different levels of education, from high-school dropouts (column 4) to a graduate degree (column 8).[13] The impact of immigration on the wage of native workers is monotonically increasing with their level of education: the effect is nil for high school dropouts (column 4), and increases by one order of magnitude going from a high school degree (column 5, $\beta = 0.017, s.e. = 0.005$) to a graduate degree (column 8, $\beta = 0.247, s.e. = 0.085$). The impact of immigration on college graduates (column 7, $\beta = 0.085, s.e. = 0.025$) is roughly the same as the average impact for the entire population of native non-movers (column 3, $\beta = 0.108, s.e. = 0.034$).

[11] For ease of interpretation, we use adult immigration (aged 25+) as the endogenous variable in all of our regressions regarding wages and education.

[12] Potentially interesting for the interpretation of our results in the context of structural spatial growth models, we find this positive effect of immigration on wages is higher in services (non-traded sector), with a coefficient of 0.429 (s.e. 0.135), than in manufacturing (traded sector), with a coefficient of 0.211 (s.e. 0.046).

[13] We use a different horizon, 10 years instead of 5, and data from the US census instead of QCEW wage data.

High versus low education migrants. The granularity of our identification strategy in Section 2 also allows us to separately instrument for high versus low education migrants. To do so, we exploit the fact that the level of education of migrants differs by origin country, and by migration time. For example, Japanese immigrants have, on average, twice the number of years of schooling as those from Guatemala, whereas the education levels of Mexican migrants increased by about 30% during our sample period. We disaggregate our baseline instruments in (5) at origin-destination-time level, $\hat{I}_{o,d,t} = \hat{\beta}_t \cdot \hat{A}_{o,d,t-1} \times \tilde{I}_{o,-r(d),t}$, for each of the top 20 origin countries (those that send the most migrants), and generate a set of instruments for the number of years of education embodied in the migration flow from each origin to each destination.[14] The first stage for this additional endogenous variable is

$$Average\ Years\ Education_{d,t} \times Immigration_{d,t} = \delta_{s(d)} + \delta_t + \sum_{o=1}^{20} \kappa_o \hat{I}_{o,d,t} + \nu_{d,t}.$$

Because migrants from different countries at different times have different schooling levels and emigrate to different counties, we are able to isolate exogenous variation in the level of education of migrants across destinations and time. For example, other things equal, an exogenous increase of Japanese migrants to a destination induces an increase in the average education of migrants.

Table 5 panel A shows the positive impact of immigration on innovation increases with the level of education of migrants. Column 1 replicates our standard specification for the age 25+ immigration sample, with a positive - now stronger than baseline - impact of immigration on the growth of patenting per capita.[15] Column 2 adds the interaction of immigration with (demeaned) average years of schooling: more educated immigrants cause a larger increase in innovation. 10,000 migrants of average education (about 11 years) cause 2.5 more local patents per 100,000 residents to be filed in a 5-year period (10×0.254), while 10,000 migrants with one standard deviation higher education (3.7 more years of schooling) cause 13 more local patents

[14]We restrict our analysis to immigrants age 25 or older, constructing the endogenous measure of immigration at the county level for this subset of immigrants. We then interact this overall adult immigration flow with the average schooling levels of adult migrants arriving in a given county at a given time from IPUMS, which lists information on the number of years of schooling and the number of years of college education for each respondent. See Appendix A.1 for details.

[15]In column 1 of Table 5 (both panels), we consider a specification with a single endogenous regressor and multiple instruments, and therefore report the first-stage F-statistic developed in Montiel Olea and Pflueger (2013). The remaining columns in this table report results for specifications with multiple endogenous variables and multiple instruments and, to our knowledge, there is no comparable effective F-statistic in this case (Andrews et al., 2018). To nevertheless gauge our ability to identify differential exogenous variation in the separate endogenous variables, the table shows the F-Statistics from Montiel Olea and Pflueger (2013) after applying the orthogonalization procedure in Angrist and Pischke (2009) to each endogenous variable. In Column 2 of both panel A and B those F-statistics exceed the critical values for a 10% bias. In further columns the F-statistics do not always exceed the critical values, indicating possibly weak instruments.

to be filed ($10 \times (0.254 + 3.7 \times 0.281)$). Those effects are similar when controlling for county fixed effects (column 3), or when measuring years of college instead of total years of education (column 4). Column 5 uses a nonparametric measure: while the (positive) impact of migrants in the bottom tercile of education on innovation is insignificant, the impact of those in the top tercile is one order-of-magnitude larger than for immigrants with average education. The effect for the middle tercile, while lower than that for the average migrants –about half– is significantly positive. Our results are thus consistent with a large literature on the special role of educated migrants (Kerr and Lincoln, 2010; Hunt and Gauthier-Loiselle, 2010; Akcigit et al., 2017; Borjas and Doran, 2012; Moser et al., 2014; Bernstein et al., 2018), although we show innovation is not exclusively attributable to this elite group.

Table 5 panel B shows similar results for wage growth. A county receiving 10,000 migrants with average schooling would see average annual wages increase by \$300 (in 2010 dollars) over five years ($10 \times 0.298 \times \$100$), while receiving 10,000 migrants with one standard deviation higher education (3.7 more years of schooling) increases average annual wages by \$1,200 over five years ($10 \times (0.298 + 3.7 \times 0.251) \times \$100$). The effect for the top tercile of education is also one order-of-magnitude larger than for migrants with average education. This heterogeneity may partly explain the seemingly contradictory findings of the literature on the impact of immigration on wages (Borjas, 2003; Cortes, 2008; Ottaviano and Peri, 2012; Foged and Peri, 2016; Dustmann et al., 2017; Monras, 2020; Jaeger et al., 2018; Bratsberg et al., 2019).

3.4 Robustness and Additional Findings

Below, we relate our approach to ongoing debates on the merits of the shift-share approach to identification and show our results are robust to a large array of alternative specifications.

Randomization tests. Appendix Table 2 implements a randomization test developed by Adão et al. (2019) to gauge whether our instrument suffers from an over-rejection problem typical of shift-share designs:[16] two US counties with similar pre-existing ancestry may also

[16]To clarify the comparison, the shifts are industry shocks in Adão et al. (2019) versus immigration shocks in our case; the shares are employment shares in Adão et al. (2019) versus ancestry shares in our case; the variation is at the sector-commuting zone level in Adão et al. (2019), versus country-county in our case.

To implement the procedure as in Adão et al. (2019), we replace ancestry in levels with ancestry shares. Formally, using predicted ancestry $\hat{A}_{o,d,t-1}$ from (2), equation (4) becomes

$$I_{o,d,t} = \delta_{o,r(d)} + \delta_{c(o),d} + \delta_t + X'_{o,d}\theta + b_t \cdot [\frac{\tilde{A}_{o,d,t-1}}{\sum_{d'} \tilde{A}_{o,d',t-1}} \times \tilde{I}_{o,-r(d),t}] + u_{o,d,t},$$

where the normalization $\tilde{A}_{o,d,t-1} = \hat{A}_{o,d,t-1} - \min[0, \min_{d'}[\hat{A}_{o,d',t-1}]]$ ensures predicted shares are in $[0, 1]$.

have similar exposure to other (unobservable) economic forces, leading to a dependency across residuals not accounted for by conventional clustered standard errors. We randomly generate immigration 'shift' shocks for each $\{o, r, t\}$ country-region-time triplet and construct placebo instruments by interacting these random shocks with our predicted ancestry shares, and run 1,000 placebo regressions of actual immigration on our randomly generated instrument. Column 1 reports the fraction for which we reject the null hypothesis of no effect at the 5% statistical significance threshold. We find a false rejection rate of 3.8% – close to the theoretical asymptotic 5% level, suggesting our inference based on conventional clustered standard errors is valid.

The remaining columns show that using predicted rather than realized ancestry to construct our instruments is key. Column 2 uses *realized* past immigration shares as in Card (2001). The false rejection rate of 27% is a sign of unreliable inference. Column 3 shows the same problematic result, a false rejection rate of 25%, when using realized ancestry shares.[17] The correlation between local economic factors and ancestry shares invalidates inference with standard shift-share instruments, but not with our predicted-ancestry instrument.

Realized versus predicted ancestry, state versus county aggregation. We explore in Appendix Table 4 the difference in point estimates between using our instrument with predicted ancestry shares (column 1) versus a conventional shift-share instrument with realized ancestry shares (column 2). The estimated impact of immigration on innovation is similar using either instrument, despite the fact that the conventional shift-share instrument suffers from over-rejection (Appendix Table 2). The estimated impact of immigration on innovation is also similar when we aggregate our data at the US State level as in Hunt and Gauthier-Loiselle (2010), though the estimated standard error using our predicted ancestry instrument (column 3) is again larger than with a conventional shift-share instrument (column 4).

Alternative Instruments. Appendix Table 5 panel A explores the robustness of our main finding to alternative constructions of our instrument: column 1 replaces the push factor in (2), the number of migrants from foreign origin o excluding those who settle in the region where domestic county d is located, with the number of migrants from o excluding those who settle in counties with migrations that are serially correlated with those to d;[18] column 2 replaces the pull factor in (2), the share of European migrants who settle in d, with the share of migrants

[17] Appendix Table 3 presents additional statistics from the randomization test of Adão et al. (2019).

[18] For each pair of counties, we compute the correlation coefficient over time of total immigration (from all origin countries) and exclude from the push factor at t for county d all migrations to counties d' if their correlation with d is positive and statistically significant at the 5% level.

from a continent different than o's who settle in d; column 3 freezes predicted ancestry at its 1975 level in the construction of our instrument in (5); and column 4 uses non-European immigration until 1960 only to predict pre-existing ancestry. Our estimate for β varies little across specifications. Panel B shows the same stability of the estimated impact of immigration on innovation measured as an elasticity, β_{IHS}, using the IHS-IHS specification in (7).

Additional robustness checks. Appendix Table 6 shows that our instrument separately identifies significant variation in contemporaneous immigration, even when controlling for lagged immigration shocks. It does so despite the high level of serial correlation in immigration (Jaeger et al., 2018). This pattern is comforting for our identifying assumption and is also consistent with our finding in Section 4 that our immigration shocks are not confounded by persistent productivity shocks. Appendix Table 7 shows our results are robust to weighting by the citation counts of patents to account for differences in patent quality. Appendix Table 8 shows a permutation test, randomly reassigning the baseline instrument within various sets of observations. Across all permutation tests, we find no effect of this permuted instrument on immigration, no reduced-form impact of this permuted instrument on innovation, and the right hand side rejection rate is small (always below 5.2%). Appendix Table 9 shows results similar to our baseline specification for the impact of population growth on innovation, using our immigration shocks in (5) as an instrument for population growth. Appendix Table 10 shows our coefficient is stable to including 'bad controls': population density in 1970, patents per capita in 1975, and the share of high school or college educated in 1970. Appendix Table 11 shows our results are not driven by individual origin countries. In panel A we repeat the exercise in Table 3 removing one country at a time (for the 5 largest immigrant origin countries, Mexico, China, India, the Philippines, and Vietnam). In panel B, we use *only* migrants from each one of those 5 countries. The estimate for the impact of immigration on innovation varies little across samples.

Domestic versus Immigrant Innovators. Appendix Table 12 shows our results are not mechanically driven by incoming immigrant inventors. We define an inventor who files a patent in the US as "domestic" if their first patent is filed with a US address and as "immigrant" otherwise. Doing so requires assigning patents to counties based on the location of inventors, rather than assignees as in our baseline specification. Column 1 shows this alternative assignment does not alter our baseline finding: our estimate of β in (1) is 0.098 (s.e.=0.038) compared to 0.122 (s.e.=0.045) in Table 3. Column 2 shows the vast majority of the effect of immigration on innovation, about 80% (0.079/0.098), comes from domestic inventors. Columns 3 and 4 show immigrant inventors and mixed teams of domestic and immigrant inventors contribute the remaining shares of the overall effect (5% and 10% respectively). So while a prolific literature has shown the crucial role foreign inventors play in US innovations (Akcigit et al., 2017; Arkolakis et al., 2020; Bernstein et al., 2018; Borjas and Doran, 2012; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Khanna and Lee, 2018; Moser et al., 2014, 2021; Stuen et al., 2012), we find the aggregate (county-level) response to immigration shocks primarily comes from domestic innovators. Although the contribution of patent flows from immigrant and domestic-immigrant inventor teams induced by immigration is large relative to their overall share of total US patents (1% and 4%, respectively), it constitutes a small share of the aggregate response.[19]

This stylized fact motivates our modeling choice in Section 4, where the impact of immigration on innovation is driven by scale effects in the production of ideas, and where we abstract from differentiation in foreign-born versus native inventors.

Spatial spillovers. Appendix Table 14 shows positive spatial spillovers of immigration on innovation (panel A) and wage growth (panel B). We consider three concepts of geographic spillovers, and construct distinct instruments for each: within-state spillovers; spillovers that decay smoothly with distance;[20] and immigration within 100km (60 miles), between 100km and 250km (150 miles), between 250km and 500km (300 miles), and beyond 500km. In panel A column 1, we first show that the effect of immigration on innovation is similar with state fixed effects (0.122, s.e.=0.045, our baseline in Table 3) and census division fixed effect (0.137, s.e.=0.048). Immigration within county d's state, excluding d, has a positive impact on local innovation in d (column 2). Immigration to neighboring counties (inversely weighted by distance) also has a positive impact (column 3). And a one standard deviation increase in immigration within 100km of d doubles innovation in d relative to the mean; but immigration beyond 100km has no impact (columns 4). We successfully identify independent variations in immigration at each level of aggregation, one of the strengths of our identification method.[21]

The spatial spillovers for wage growth in panel B are similar.

Interestingly, we also show in Appendix Table 16 that immigration causes an inflow of

[19]In Appendix Table 13, we further limit to patents in which all domestic inventors have a patent filed in the US prior to period t (column 3) and further to those with a prior patent in the same county (column 4). The impact of immigration on patenting is similar whether we include innovators who move (column 3) or exclude them (column 4), suggesting our results are not driven by an influx of domestic innovators.

[20]We sum immigration shocks to all counties other than d, inversely weighted by their great circle distances from d computed from county centroids using the census mapping files for county geographies.

[21]Appendix Table 15 displays the corresponding first-stage regression results. For all specifications involving multiple endogenous variables, we use the Angrist and Pischke (2009, p. 217-218) first-stage F-statistic, separately testing for each regressor the null of weak identification.

natives (both whites and non-whites). This suggests that natives endogenously respond to the anticipated positive impact of immigration on innovation and wages. Our structural model in Section 4 features such endogenous internal migrations driven by expected wage differentials.

Dynamism. Appendix Table 17 shows immigration also increases dynamism –the job creation and destruction rates, and the skewness of the job growth rate across sectors– consistent with endogenous growth theories with Schumpeterian creative destruction linked to innovation (Aghion and Howitt, 1992; Grossman and Helpman, 1991; Klette and Kortum, 2004).

4 Structural Model and Estimation

We interpret our main finding that immigration shocks have a positive causal effect on local innovation and wages at the 5-year horizon through the lens of a quantitative regional equilibrium model of endogenous growth and migrations.

4.1 Model

There are O countries and D counties. Upon arriving in the US, migrants form rational expectations and endogenously select a destination to maximize their one-period ahead utility, just as natives choose where to live. Time t is discrete, and corresponds to the five-year intervals in our data. Each county produces a nationally traded final good (Y) and patents/ideas (Q).

Goods production. The final good $Y_{d,t}$, with price normalized to 1, is produced by a representative firm in county d at time t with technology

$$Y_{d,t} = Z_{d,t} Q_{d,t} L^{\alpha}_{Y,d,t}, \tag{8}$$

where $Q_{d,t}$ is the number (stock) of patents/ideas used in production, $L_{Y,d,t}$ is labor used for production, and $\alpha \in (0, 1)$ is the elasticity of output to production labor. $Z_{d,t}$ is a stationary exogenous total factor productivity shock and evolves according to $\ln Z_{d,t} = \rho \ln Z_{d,t-1} + \epsilon_{d,t}$, with autocorrelation $\rho \in (0, 1)$ and normally distributed innovations $\epsilon_{d,t} \sim \mathcal{N}(0, \sigma^2_{\epsilon})$.

Ideas production. The stock of patents/ideas in d evolves cumulatively, $Q_{d,t} = Q_{d,t-1} + N_{d,t}$, where $N_{d,t}$ new patents are produced by combining research labor and existing patents,

$$N_{d,t} = L^{\gamma}_{N,d,t} Q^{1-\gamma}_{d,t-1}. \tag{9}$$

$L_{N,d,t}$ is labor used for creating new patents, and $\gamma \in (0,1)$ is our key parameter: the elasticity of innovation to research labor. $N_{d,t}$, the flow of new ideas, corresponds to the total number of patents issued in d at t. The structure of the innovation production function in (9) places our model within a broadly defined class of semi-endogenous growth models (Jones, 1995): diminishing returns to past ideas in innovation require that the supply of researchers increases over time to generate sustained growth. In this class of models, the supply of researchers, which can shift through immigration shocks, is the key driver of innovation.

Firms. The markets for goods and patents are competitive, with price-taking firms. The final goods firm in d combines new patents N and production labor L_Y to maximize profits,

$$\max_{N,L_Y} Z_{d,t} \left(N + Q_{d,t-1}\right) L_Y^{\alpha} - W_{d,t} L_Y - p_{d,t} N, \tag{10}$$

while the research firm optimally chooses research labor inputs L_N to maximize

$$\max_{L_N} p_{d,t} L_N^{\gamma} Q_{d,t-1}^{1-\gamma} - W_{d,t} L_N. \tag{11}$$

The local wage $W_{d,t}$ and the price of a local patent $p_{d,t}$, determined in equilibrium, are taken as given by both types of firms. The research firm gains ownership of the patents it produces for a single period. In the next period, patents expire and become a public good for other firms in the county.[22] This simplifying assumption ensures the research firm makes only static decisions, increasing tractability despite the rich underlying growth dynamics.

Population and immigration. In each county d, a mass $L_{d,t}$ of current residents each supplies one unit of labor to their local labor market alone. The local labor force evolves as foreign and domestic migrants arrive and leave, $L_{d,t+1} = (1-\mu)L_{d,t} + \sum_{o=1}^{O} I_{o,d,t} + \sum_{d'=1}^{D} M_{d',d,t}$, where $I_{o,d,t}$ is the number of foreign immigrants from country o who settle in county d at time t, and $M_{d',d,t}$ is the number of domestic movers from d' to d at t. Only a fraction μ of domestic residents are given a chance to move any period, so the total gross outflow of domestic movers from d' is $\mu L_{d,t}$. The total number of migrants from origin o to the US, $I_{o\cdot,,t} = \sum_{d=1}^{D} I_{o,d,t}$, grows at a rate n, $I_{o\cdot,,t} = (1+n)^t \exp\left(\nu_{o,t}\right)$, subject to log-normally distributed exogenous shocks, $\nu_{o,t} \sim \mathcal{N}\left(0, \sigma_\nu\right)$. These correspond to the origin-specific 'push' shocks in our empirical analysis. Note the one-period "time to migrate," which mimics the way we construct our data.

[22] We show in Section 3.4 that our results are similar if we allow patents to fully diffuse *nationally*.

Upon their arrival in the US at t, migrant i from o forms rational expectations about wages and ancestry compositions and settles in destination d where they derive the highest utility,

$$d = \arg\max_{k} \mathbb{E}_t \left[W_{k,t+1}^{\lambda} \left(\frac{A_{o,k,t+1}}{A_{o,\cdot,t+1}} \right)^{1-\lambda} \right] \exp\left(-\tau_{o,k,t}\right) \eta_{k,t}\left(i\right), \tag{12}$$

where $W_{k,t+1}$ is the future wage in destination k, $A_{o,k,t+1}/A_{o,\cdot,t+1}$ is the ancestry share from origin o who will reside in k at $t+1$ (with $A_{o,t+1} = \sum_{d=1}^{D} A_{o,d,t+1}$), $\eta_{k,t}\left(i\right)$ are i.i.d. extreme-value distributed preference shocks with dispersion parameter θ,[23] and $\tau_{o,k,t} \sim \mathcal{N}\left(0, \sigma_{\tau}^{2}\right)$ are i.i.d. normal shocks to bilateral migration costs from o to k.

The stock of residents in d with ancestry from o evolves recursively as migrants and domestic residents with ancestry from o arrive and leave, $A_{o,d,t+1} = (1-\mu)A_{o,d,t} + I_{o,d,t} + \sum_{d'=1}^{D} M_{o,d',d,t}$, where $M_{o,d',d,t}$ are domestic residents with ancestry o who move from d' to d at t (with $M_{d',d,t} = \sum_{o} M_{o,d',d,t}$). Other things equal, migrant i is more likely to settle in d if they expect a high real wage there $(W_{d,t})$[24] and expect d to host a large community of common ancestry $(A_{o,d,t+1}/A_{o,\cdot,t+1})$, if the bilateral migration cost is low $(\tau_{o,d,t})$, and if they draw a high taste shock $(\eta_{d,t}\left(i\right))$. $\lambda \in [0,1]$ governs the relative importance of economic versus social factors in this decision.

Assuming a continuum of migrants, the share of migrants from o who chose destination d is

$$I_{o,d,t} = I_{o,\cdot,t} \frac{\exp\left(-\theta\tau_{o,d,t}\right) \left(\mathbb{E}_t \left[W_{d,t+1}^{\lambda} \left(\frac{A_{o,d,t+1}}{A_{o,\cdot,t+1}} \right)^{1-\lambda} \right] \right)^{\theta}}{\sum_{k=1}^{D} \exp\left(-\theta\tau_{o,k,t}\right) \left(\mathbb{E}_t \left[W_{k,t+1}^{\lambda} \left(\frac{A_{o,k,t+1}}{A_{o,\cdot,t+1}} \right)^{1-\lambda} \right] \right)^{\theta}}. \tag{13}$$

This expression intuitively links to our reduced-form migration model in Section 2. There is a large inflow of migrants from o to d if (i) many migrants from o arrive in the US, $I_{o,\cdot,t}$ large (a 'push' factor), (ii) d offers a high expected wage, $W_{d,t+1}$ high, (iii) the migration cost from o to d is low, $\tau_{o,d,t}$ low ('economic pull' factors, potentially giving rise to the *reverse causality* and *county-country omitted factors* concerns described above), and (iv) there is a large expected group with ancestry from o in d, $A_{o,d,t+1}/A_{o,\cdot,t+1}$ large (a 'social pull' factor as in Card, 2001).

Domestic resident j from d' of ancestry o, when given an i.i.d. chance to move with probability μ, makes a similar internal migration decision, choosing optimally where to settle,

$$d = \arg\max_{k} \mathbb{E}_t \left[W_{k,t+1}^{\lambda} \left(\frac{A_{o,k,t+1}}{A_{o,\cdot,t+1}} \right)^{1-\lambda} \right] \tilde{\eta}_{k,t}\left(j\right), \tag{14}$$

[23] The idiosyncratic taste shocks are distributed Frechet, with $\Pr\left[\eta_{k,t}\left(i\right) \leq \eta\right] = \exp\left(-\eta^{-\theta}\right), \forall i, k, t$.

[24] Given that goods are freely traded on a national US market, wages in units of the numeraire are real wages, and directly comparable across locations.

where $\tilde{\eta}_{k,t}(j)$ is again an i.i.d. extreme value distributed shock with dispersion parameter θ. The number of residents with ancestry o who move from d' to d at t is,[25]

$$M_{o,d',d,t} = \mu A_{o,d',t} \frac{\left(\mathbb{E}_t\left[W_{d,t+1}^{\lambda}\left(\frac{A_{o,d,t+1}}{A_{o,\cdot,t+1}}\right)^{1-\lambda}\right]\right)^{\theta}}{\sum_{k=1}^{D}\left(\mathbb{E}_t\left[W_{k,t+1}^{\lambda}\left(\frac{A_{o,k,t+1}}{A_{o,\cdot,t+1}}\right)^{1-\lambda}\right]\right)^{\theta}}. \tag{15}$$

Local labor is allocated to goods and new ideas production, $L_{d,t} = L_{Y,d,t} + L_{N,d,t}$. Given our convenient timing assumptions for patent ownership and migrations, migrants and residents make no dynamic decisions, so we do not model household preferences further.

4.2 Equilibrium and Estimation

We characterize the deterministic balanced growth path equilibrium analytically and numerically solve for dynamics off the balanced growth path with each period equal to 5-year as in our data. See Appendix B.1 for details and a formal definition of the equilibrium.

Equilibrium properties. Figure 1 displays impulse response functions to a temporary, exogenous, inflow of migrants arriving in a given destination (top-left panel), for different values of γ: our baseline estimate $\gamma = 0.781$ (solid line) and a lower value $\gamma = 0.5$ (dashed line). The endogenous responses depict deviations from the balanced growth path.

The influx of migrants mechanically increases the local labor force (top-right panel). Due to the cumulative impact of immigration, with past immigrant enclaves attracting future migrants, and the sluggish nature of deterministic population growth, this increase is persistent. Those additional workers expand the research sector, and patenting increases for multiple periods (bottom-left panel). The key parameter governing the strength of the innovation response to immigration is the local elasticity of innovation to research labor, γ. The smaller γ (dashed versus solid lines), the weaker the impact of immigration on innovation. This motivates our choice to use the reduced-form causal impact of immigration on innovation to identify γ.

Immigration has two competing effects on wages (bottom-right panel): on the one hand, the increased abundance of local labor exerts a downward pressure on wages, a negative neo-classical labor-supply channel; on the other hand, higher local innovations increase the marginal product of labor and wages, a positive endogenous-growth channel. At our estimated parameters (solid

[25] Note that since we do not assume any county-specific internal migration frictions, all domestic migrants make similar choices on average. The share of domestic migrants from origin county d' of ancestry o who settle in d is the same as for any other origin county d'': $M_{o,d',d,t}/\left(\mu A_{o,d',t}\right) = M_{o,d'',d,t}/\left(\mu A_{o,d'',t}\right), \forall\left(d', d''\right)$.

line), the positive effect dominates at the 5-year horizon, consistent with our empirical results. For lower values of γ (dashed line), wages initially decline due to the increased labor supply, but eventually increase as innovations accumulate.

This simple intuition may explain the mixed results in the empirical labor literature on immigration and wages (Borjas, 2003; Cortes, 2008; Ottaviano and Peri, 2012; Foged and Peri, 2016; Dustmann et al., 2017; Monras, 2020; Jaeger et al., 2018; Bratsberg et al., 2019): whether the negative neo-classical impact on wages of a labor supply increase, or the positive endogeneous-growth effect dominates, depends on the size of local scale effects and the time horizon.[26]

Estimation results. We use a simulated method of moments (indirect inference) to estimate the model. In addition to a range of conventional moments, including the volatility and persistence of immigration, output, and patent flows, we target the IV estimate of the elasticity of innovation to immigration, β_{IHS} (column 4 in Table 3). We use the same identification strategy to construct an instrument for immigration in our simulated model as in the data.

Table 6 presents results from our structural estimation, including point estimates, standard errors, and the model's fit.[27] We match our target moments well (panel A). In particular, the elasticity of innovation to immigration β_{IHS} is close in our simulated model and in the data (1.641 versus 1.652). Our structural estimate for the local elasticity of patenting to research labor ($\gamma = 0.781$, $s.e. = 0.086$ in panel B) lies at the upper end of the range of values typically used in calibrated models of aggregate endogenous growth and firm innovation (Acemoglu et al., 2018; Bloom et al., 2021; Akcigit et al., 2020; Blundell et al., 2002; Terry et al., 2020).

Table 6 also reports our estimates of other parameters, which are intuitive. We estimate highly persistent local productivity processes with an annual autocorrelation of $\rho^{1/5} = 0.971$, matching the high persistence of GDP and patenting at the local level. This high persistence of local shocks represents a major threat to identification of conventional shift-share instruments, even when they rely on ancestry or immigration shares from the distant past. We also estimate

[26] This intuition is complementary to Jaeger et al. (2018), where the gradual inflow of capital in response to a labor shock plays a role similar to endogenous innovation in our model. The key qualitative difference is that capital accumulation induces a temporary rise in real income and a subsequent decrease, while the innovation response in our model yields permanent gains.

[27] We estimate 5 parameters $(\gamma, \rho, \sigma_\epsilon, \sigma_\nu, \sigma_\tau)$, targeting 6 moments (our IV coefficient β_{IHS}, the s.d. of origin immigration $I_{o,\cdot,t}$, the s.d. of destination immigration $I_{d,t}$, the s.d. of origin-destination immigration $I_{o,d,t}$, the autocorrelation of output per capita, the autocorrelation of patenting). For computational tractability, we simulate our model over $T = 1,000$ periods for $O = 10$ foreign regions and $D = 9$ domestic regions. We set the population growth rate to $n = 2\%$, the labor elasticity in production $\alpha = 0.8$ to match average markups of 20%, $\lambda\theta = 0.5$ from Caliendo et al. (2019) with $\lambda = 0.5$ and $\theta = 1$, and the 5-year mobility shock $\mu \approx 0.25$ to match the annual county-to-county gross mobility rate of 5% within the US. Further technical details on the estimation are in Appendix B.2.

that shocks to county-level productivity are less volatile ($\sigma_\epsilon = 0.020$) than shocks to origin-level immigration flows ($\sigma_\nu = 0.595$) or bilateral immigration costs ($\sigma_\tau = 0.520$), matching the relative volatilities of immigration at the county, origin, and county-origin levels.

The dynamics of innovation and wages. Figure 2 shows the elasticity of patenting to research labor allows us to qualitatively match the *untargeted* dynamic response of both innovation and wages to a local immigration shock. The top panel A shows the impulse response of innovation and wages to a one period inflow of migrants in our model. The bottom panel B shows the response of patenting and wages to an exogenous immigration shock over different horizons (5-, 10-, and 15-year), controlling for intermediate immigration shocks. The elasticity of wages to immigration is approximately equal to 0.13.[28] In both model and data, immigration has a positive and persistent impact on local innovation and wages, even though we only target the contemporaneous response of innovation, and we do not target the wage response at all.

4.3 Quantification of the Aggregate Impact of Immigration

We compute a simple aggregate counterfactual to gain intuition for the magnitudes involved. We simulate the trajectory the US might have followed had the Immigration and Nationality Act of 1965 (INA) not been passed. This act lifted many immigration restrictions. Comparing a high realized migration path with the INA, to a counterfactual lower migration path without, we offer suggestive evidence on the quantitative impact of immigration on innovation and growth.

To simulate the dynamics of the economy in a hypothetical world where the INA would not have passed, we feed negative immigration shocks each period ($\nu' s$) such that the total population growth rate is 16% lower than in our calibrated model. This 16% reduction is computed to approximate the lower contribution of immigrants to US population growth over 1860-1960, before the INA, compared to 1970-2010, after the INA (see Appendix B.3 for details).[29]

The resulting cumulative deviations of macroeconomic aggregates from the balanced growth path are presented in Figure 3. The left panel shows the cumulative reduction in the labor force. Our estimates suggest this counterfactual reduction in immigration would have caused a sharp reduction in patenting per capita, reaching a 6% drop by 1990 (right panel, dotted line). Interestingly, the impact on output per capita is close to zero until 1980, as the large stock of patents inherited from the pre-INA period, and the reallocation of labor away from innovation

[28] Appendix Table 18 shows the corresponding estimation results.

[29] We do not claim to have quantified the causal impact of the INA on immigration. This exercise is solely meant as an illustration of the quantitative magnitudes in our model. We use demographic data only to get a *plausible* magnitude for reduced immigration in a hypothetical world without the INA.

due to the reduction in immigration, allow for more goods production; eventually, as the stock of innovation falls, output per capita falls by 5% by 2010 (right panel, solid blue line).

This estimated impact, about 5% lower output per capita over 45 years, lies within the range of recent quantitative estimates in the endogenous growth literature. For example, the recent decline in *total* US population growth contributes about 19% over 45 years (Peters and Walsh, 2021), increased growth from trade generates 45-year gains of around 7% (Sampson, 2016), short-termist incentives on US managers cost around 2% over 45 years (Terry, 2023), and stronger US antitrust policy generate 45-year gains of around 4% (Cavenaile et al., 2023). The ratio of the cumulative population effects to cumulative output per capita effects, a bit more than 2-to-1 in our analysis, also roughly matches a similar exercise in an earlier historical period in Arkolakis et al. (2020).

4.4 Identification

Our structural model allows us to compare our reduced-form identification strategy (Section 2) to the seminal identification strategy proposed by Card (2001), which predicts contemporaneous immigration shocks by interacting immigration shifters with past immigration shares,

$$\hat{I}^{Card}_{\cdot,d,t} = \sum_{o=1}^{O} I_{o,\cdot,t} \frac{I_{o,d,t-1}}{I_{o,\cdot,t-1}}. \tag{16}$$

Applying our endogenous migration model (13) at time $t-1$, we see that past immigration shares ${}^{I_{o,d,t-1}}/_{I_{o,\cdot,t-1}}$, and hence predicted immigration shocks in d themselves, $\hat{I}^{Card}_{,d,t}$, are driven by period $t-1$ expectations of future wages and ancestry terms in destination d. But a positive productivity shock, an increase in $Z_{d,t-1}$ in (8), increases not just contemporaneous wages, $W_{d,t-1}$, but also expected future wages, $W_{d,t}$, because of the persistence in productivity. The same reverse causality logic also applies to innovations: a positive productivity shock, $Z_{d,t-1}$ higher, attracts migrants and triggers innovations, which in turn increases future innovation through the production function (9). The 'Card instrument' in (16) is thus contaminated by the (simple) *reverse causality* effect of wages and innovation on immigration due to persistent productivity shocks.[30] Our identification strategy instead constructs a set of instruments for ancestry, $\hat{I}_{\cdot,d,t} = \sum_{o=1}^{O} \hat{b}_t[\hat{A}_{o,d,t-1} \times \tilde{I}_{o,leave-out,t}]$ in (5), which isolate *relative* variations in predicted local ancestry that result exclusively from the coincidental timing of historical push and pull factors – purging the effect of persistent productivity shocks from our immigration shocks.

[30] As noted earlier, David Card explicitly notes that past immigration shares may be correlated with persistent productivity shocks (Card, 2001, p. 43), potentially creating a spurious correlation with contemporaneous wages.

Figure 4 (left panel) explicitly shows the correlation structure between productivity shocks ($Z_{d,t}$), realized immigration ($I_{\cdot,d,t}$), the 'Card' predicted immigration shock ($\hat{I}^{Card}_{\cdot,d,t}$), and our proposed predicted immigration shock ($\hat{I}_{\cdot,d,t}$). For reference, the figure also includes an intermediate 'Ancestry' version of our instrument $\hat{I}^{Anc}_{\cdot,d,t}$ constructed by replacing predicted ancestry $\hat{A}_{o,d,t-1}$ with realized ancestry. As expected, because productivity is persistent, realized immigration is correlated with contemporaneous productivity shocks. The 'Card' instrument, because it relies on past immigration shares, themselves correlated with persistent past productivity shocks, is also correlated with contemporaneous productivity shocks. Using realized ancestry, the 'Ancestry' instrument, alleviates this correlation somewhat but not fully. Our predicted immigration shocks $\hat{I}_{\cdot,d,t}$, which exploit only the historically predicted, relative component of ancestry and include a rich leave-out structure, are not correlated at all with local productivity shocks.

The right panel shows our identification strategy is also immune to the more elaborate identification concern regarding *county-country specific omitted factors*. If specific migrants (say Indian engineers) have skills suited for certain industries and destinations (say IT in Silicon Valley), then any shock to the cost of migration correlated with TFP (say $\tau_{India,Santa\,Clara,t}$ correlated with $Z_{Santa\,Clara,t}$) would induce a spurious correlation between innovation, immigration, and ancestry. Figure 4 (right panel) confirms that realized bilateral migration flows ($I_{o,d,t}$), 'Card' predicted bilateral migration flows ($\hat{I}^{Card}_{o,d,t}$), and crude 'Ancestry' instruments' predicted migration flows ($\hat{I}^{Anc}_{o,d,t}$) are all correlated with the model's underlying bilateral migration cost shocks ($\tau_{o,d,t}$). By contrast, our predicted migration flows ($\hat{I}_{o,d,t}$) are not.

To summarize, within a quantitative model of endogenous growth and migration, our predicted immigration shocks are orthogonal to two variables that would raise endogeneity concerns (persistent productivity and bilateral migration costs). This bolsters our confidence that our identification strategy is well-suited to identify the causal impact of immigration on innovation.

4.5 Robustness

We conclude with an exploration of the robustness of our results to various extensions.

Local versus global idea spillovers. In our baseline model, local innovations only depend on local research labor and the local stock of ideas. Our empirical results suggest some degree of spatial diffusion. Our results are robust to allowing for spatial spillovers: going to an extreme case of full (national) spillovers in ideas after one period, the estimated local innovation elasticity γ in Appendix Table 19 changes little and remains around 0.8. Intuitively, spillovers affect the slow-moving stock of ideas, but have little impact on the short-run response of local innovation to immigration shocks (see Appendix Figure 5). Spatial spillovers thus do not affect our quantification of the aggregate response to a national symmetric immigration shock. They affect instead the distribution of innovation and wage growth across regions in response to asymmetric shocks, which we do not explicitly study here.

Decreasing returns to labor. The parameter governing the degree of decreasing returns to scale in production, α, has both a literal labor elasticity role as well as, in some alternative interpretations of the model, a role in governing implied markups. In our baseline we choose $\alpha = 1/1.2 \approx 0.8$ to match a 20% implied markup. Appendix Figure 6 shows that the impact of an immigration shock is robust to alternative choices for α over the wide range 0.7 to 0.95. The impact of an immigration shock on innovation remains strong in each case.

Constant versus decreasing returns in research. Our model is a semi-endogenous growth model in the sense that per capita income growth is proportional to population growth in steady state. In our baseline we chose a particular technology for the research sector with constant returns to scale ($N_{d,t} = L_{N,d,t}^{\gamma} Q_{d,t-1}^{1-\gamma}$) implying an elasticity of innovation to past ideas of $1 - \gamma \approx 0.2$. We explore alternative specifications for the production function of new ideas ($N_{d,t} = L_{N,d,t}^{\gamma} Q_{d,t-1}^{\zeta}$ allowing $\gamma + \zeta \neq 1$), set ζ to 0.1 and 0.3, evenly spaced around our baseline of $\zeta \approx 0.2$, and re-estimate the model in each case to recover γ. The estimated returns to scale to innovation, $\gamma + \zeta$, are near unity in each specification.[31] Appendix Figure 7 shows the impact of an immigration shock across specifications. A higher elasticity ζ to the slow-moving idea stock unsurprisingly results in stronger long-run impacts while dampening short-run impacts. Over 45 years, the horizon of our INA analysis in Figure 3, the impact of immigration on innovation is similar across specifications.

Conclusion

The economic, social, political, and cultural changes immigrants bring to their host communities are the subject of fierce political controversies. Informing this debate with data has proven difficult, not only because different migrants may affect their host communities in different ways, but also due to an identification problem: immigrants likely choose to settle in host communities that offer the best prospects rather than at random. This generates endogenous

[31]We estimate $\hat{\gamma} = 0.8250$ when $\zeta = 0.1$ and $\hat{\gamma} = 0.6995$ when $\zeta = 0.3$.

correlations between past and present immigration, and local economic outcomes, making it difficult to isolate the causal effects of immigration.

We introduce a novel solution to this identification problem that allows for the construction of local immigration shocks – instruments for the total number of migrants arriving in each US county for each five-year period since 1975. Importantly, these immigration shocks remain valid even if migrations prior to 1975, and thus the county's pre-existing ancestry composition, are endogenous to local economic activity, and can be flexibly disaggregated into different instruments for migrations from each origin country to each destination county in each period.

We use these instruments to show that, on average, immigration to the US between 1975 and 2010 had a positive causal effect on local innovation and average wages of natives. For example, a 1% increase in immigration to a given county on average increases, over a five-year period, the number of patents filed by local residents by 1.6% and local wages by 0.13%.

We interpret those empirical results through the lens of a structural model of endogenous migrations and innovation. To quantify this structural model, we target the reduced form impact of immigration on innovation. This quantification exercise suggests that the elasticity of innovation with respect to research labor, 0.8, is relatively large, implying that labor supply shocks such as those brought by international migrations have strong scale effects on local innovation. This model also explicitly shows that while immigration unambiguously increases innovation, its effect on local wages varies over time: in the very short run, it is possible for a labor supply shock to depress wages, while the positive impact of higher innovation and labor productivity on wages gradually builds over time and becomes dominant.

Beyond our application to immigration, we believe our approach linking pre-existing (ancestry) shares to the interaction of historical factors may prove useful in other applications of the canonical shift-share instrument. For example, the cumulative forces that lead to the establishment of migrants of different ethnicities across locations may be similar to the historical forces that generate variation in pre-existing shares of industries, occupations, and other specializations across locations. Our procedure for isolating quasi-random variation in pre-existing shares may thus prove useful in other settings that have studied the local effects of import competition, the local fiscal multiplier, local supply elasticities, and other important subjects.

References

Abramitzky, R. and L. Boustan (2017): "Immigration in American economic history," *Journal of Economic Literature*, 55, 1311–45.

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. Kerr (2018): "Innovation, reallocation, and growth," *American Economic Review*, 108, 3450–91.

Adão, R., M. Kolesár, and E. Morales (2019): "Shift-share designs: Theory and inference," *The Quarterly Journal of Economics*, 134, 1949–2010.

Aghion, P. and P. Howitt (1992): "A model of growth through creative destruction," *Econometrica (1986-1998)*, 60, 323.

Akcigit, U., J. Grigsby, and T. Nicholas (2017): "The rise of American ingenuity: Innovation and inventors of the Golden Age," NBER Working Paper 23047.

Akcigit, U., J. G. Pearce, and M. Prato (2020): "Tapping into talent: Coupling education and innovation policies for economic growth," NBER Working Paper 27862.

Andrews, I., J. Stock, and L. Sun (2018): "Weak Instruments in IV Regression: Theory and Practice," *Annual Review of Economics*.

Angrist, J. D. and J.-S. Pischke (2009): *Mostly harmless econometrics: An empiricist's companion*, Princeton university press.

Arkolakis, C., M. Peters, and S. K. Lee (2020): "European Immigrants and the United States' Rise to the Technological Frontier," Working Paper.

Bartik, T. (1991): *Who benefits from state and local economic development policies?*, W.E. Upjohn Institute.

Bernstein, S., R. Diamond, T. McQuade, and B. Pousada (2018): "The contribution of high-skilled immigrants to innovation in the United States," Working paper.

Bloom, N., C. I. Jones, J. Van Reenen, and M. Webb (2020): "Are ideas getting harder to find?" *American Economic Review*, 110, 1104–44.

Bloom, N., P. Romer, S. J. Terry, and J. Van Reenen (2021): "Trapped factors and China's impact on global growth," *The Economic Journal*, 131, 156–191.

Blundell, R., R. Griffith, and F. Windmeijer (2002): "Individual effects and dynamics in count data models," *Journal of Econometrics*, 108, 113–131.

Borjas, G. J. (2003): "The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market," *The Quarterly Journal of Economics*, 118, 1335–1374.

Borjas, G. J. and K. B. Doran (2012): "The collapse of the Soviet Union and the productivity of American mathematicians," *The Quarterly Journal of Economics*, 127, 1143–1203.

Borusyak, K., P. Hull, and X. Jaravel (2021): "Quasi-experimental shift-share research designs," *The Review of Economic Studies*.

Bratsberg, B., A. Moxnes, O. Raaum, K.-H. Ulltveit-Moe, et al. (2019): "Opening the floodgates: Industry and occupation adjustments to labor immigration," CEPR Discussion Paper No. 13670.

Burchardi, K. B., T. Chaney, and T. A. Hassan (2019): "Migrants, Ancestors, and Foreign Investments," *The Review of Economic Studies*, 86, 1448–86.

Caliendo, L., M. Dvorkin, and F. Parro (2019): "Trade and labor market dynamics: General equilibrium analysis of the china trade shock," *Econometrica*, 87, 741–835.

Cameron, A. C. and D. L. Miller (2015): "A Practitioner's Guide to Cluster-Robust Inference," *Journal of Human Resources*, 50, 317–372.

Card, D. (1990): "The Impact of the Mariel Boatlift on the Miami Labor Market," *Industrial and Labor Relations Review*, 43, 245–257.

——— (2001): "Immigrant Inflows, Native outflows, and the Local Labor Market Impacts of Higher Immigration," *Journal of Labor Economics*, 19, 22–64.

Cavenaile, L., M. A. Celik, and X. Tian (2023): "The Dynamic Effects of Antitrust Policy on Growth and Welfare," *Journal of Monetary Economics*, 121, 42–59.

Cortes, P. (2008): "The Effect of Low-Skilled Immigration on U.S. Prices: Evidence from CPI Data," *Journal of Political Economy*, 116, 381–422.

Desmet, K., D. K. Nagy, and E. Rossi-Hansberg (2018): "The geography of development," *Journal of Political Economy*, 126, 903–983.

Dustmann, C., U. Schönberg, and J. Stuhler (2017): "Labor supply shocks, native wages, and the adjustment of local employment," *The Quarterly Journal of Economics*, 132, 435–483.

Foged, M. and G. Peri (2016): "Immigrants' effect on native workers: New analysis on longitudinal data," *American Economic Journal: Applied Economics*, 8, 1–34.

Giannone, E. (2019): "Skill-biased technical change and regional convergence," Working paper.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020): "Bartik instruments: What, when, why, and how," .

Grossman, G. M. and E. Helpman (1991): "Quality ladders in the theory of growth," *The Review of Economic Studies*, 58, 43–61.

Guren, A., A. McKay, E. Nakamura, and J. Steinsson (2021): "What Do We Learn from Cross-Regional Empirical Estimates in Macroeconomics?" *NBER Macroeconomics Annual*, 35, 175–223.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001): "The NBER Patent Citaitons Data File: Lessons, Insights, and Methodological Tools," NBER Working Paper 8498.

Hanson, G. H. (2009): "The economic consequences of the international migration of labor," *Annual Review of Economics*, 1, 179–208.

——— (2010): "Future Directions for Research on Immigration," *American Economic Association, Ten Years and Beyond: Economists Answer NSF's Call for Long-Term Research Agendas.*

Hunt, J. and M. Gauthier-Loiselle (2010): "How Much Does Immigration Boost Innovation?" *American Economic Journal: Macroeconomics*, 2, 31–56.

Jaeger, D. A., J. Ruist, and J. Stuhler (2018): "Shift-share instruments and the impact of immigration," NBER Working Paper 24285.

Jones, C. I. (1995): "R&D-Based Models of Economic Growth," *Journal of Political Economy*, 103.

——— (1999): "Growth: with or without scale effects?" *American Economic Review*, 89, 139–144.

Kerr, W. R. (2008): "Ethnic scientific communities and international technology diffusion," *The Review of Economics and Statistics*, 90, 518–537.

Kerr, W. R. and W. F. Lincoln (2010): "The Supply Side of Innovation: H1B Visa Reforms and U.S. Ethnic Invention," *Journal of Labor Economics*, 28, 473–508.

Khanna, G. and M. Lee (2018): "High-skill Immigration, Innovation, and Creative Destruction," NBER Working Paper 24824.

Klette, T. J. and S. Kortum (2004): "Innovating firms and aggregate innovation," *Journal of Political Economy*, 112, 986–1018.

Lafortune, J., E. Lewis, and T. José (2019): "People and Machines: A Look at the Evolving Relationships Between Capital and Skill in Manufacturing 1860-1930 Using Immigration Shocks," *The Review of Economics and Statistics*, 101, 30–43.

Laincz, C. A. and P. F. Peretto (2006): "Scale effects in endogenous growth theory: An error of aggregation not specification," *Journal of Economic Growth*, 11, 263–288.

Lewis, E. (2011): "Immigration, Skill Mix, and Capital Skill Complementarity," *The Quarterly Journal of Economics*, 126, 1029–1069.

——— (2013): "Immigration and production technology," *Annual Review of Economics*, 5, 165–191.

Lewis, E. and G. Peri (2015): "Immigration and the Economy of Cities and Regions," in *Handbook of regional and urban economics*, Elsevier, vol. 5, 625–685.

Monras, J. (2020): "Immigration and Wage Dynamics: Evidence from the Mexican Peso Crisis," *Journal of Political Economy*, 128, 3017–3089.

Monte, F., S. J. Redding, and E. Rossi-Hansberg (2018): "Commuting, migration, and local employment elasticities," *American Economic Review*, 108, 3855–90.

Montiel Olea, J. L. and C. Pflueger (2013): "A Robust Test for Weak Instruments," *Journal of Business & Economic Statistics*, 31, 358–369.

Moser, P., S. Parsa, and S. San (2021): "Immigration, science, and invention: Evidence from the 1920s quota acts," *Unpublished manuscript*.

Moser, P., A. Voena, and F. Waldinger (2014): "German Jewish émigrés and US invention," *American Economic Review*, 104, 3222–55.

Nakamura, E. and J. Steinsson (2014): "Fiscal stimulus in a monetary union: Evidence from US regions," *American Economic Review*, 104, 753–92.

Ottaviano, G. I. and G. Peri (2012): "Rethinking the effect of immigration on wages," *Journal of the European Economic Association*, 10, 152–197.

Peretto, P. F. (1998): "Technological change and population growth," *Journal of Economic Growth*, 3, 283–311.

Peters, M. (2022): "Market Size and Spatial Growth – Evidence from Germany's Post-War Population Expulsions," *Econometrica*.

Peters, M. and C. Walsh (2021): "Population Growth and Firm Dynamics," Working Paper 29424, National Bureau of Economic Research.

Romer, P. M. (1990): "Endogenous technological change," *Journal of Political Economy*, 98, S71–S102.

Sampson, T. (2016): "Dynamic Selection: An Idea Flows Theory of Entry, Trade, and Growth," *Quarterly Journal of Economics*, 131, 315–380.

Sequeira, S., N. Nunn, and N. Quian (2020): "Immigrants and the making of America," *The Review of Economic Studies*, 382–419.

Stuen, E. T., A. M. Mobarak, and K. E. Maskus (2012): "Skilled Immigration and Innovation: Evidence from Enrolment Fluctuations in US Doctoral Programmes," *The Economic Journal*, 122, 1143–1176.

Tabellini, M. (2019): "Gifts of the Immigrants, Woes of the Natives: Lessons from the Age of Mass Migration," *The Review of Economic Studies*, 87, 454–486.

Terry, S. J. (2023): "The Macro Impact of Short-Termism," *Econometrica*, 91, 1881–1912.

Terry, S. J., T. M. Whited, and A. Zakolyukina (2020): "Information versus Investment," Working paper.

Young, A. (1998): "Growth without scale effects," *Journal of Political Economy*, 106, 41–63.

Table 1: Summary Statistics by County-Year

	N	Mean	SD	IQR
Immigration Flows and Population Change				
Immigration$_{d,t}$	21,987	1.42	12.21	0.22
Δ Population$_{d,t}$	21,986	4.02	19.64	2.54
Immigration Shock ($\hat{I}_{d,t}$)	21,987	-0.00	4.99	0.24
Patents				
Patent Flows per 100,000 people	21,987	31.27	85.21	22.08
5-Year Difference in Patent Flows (PF) per 100,000 People (Assignee)	18,846	4.61	37.77	6.35
5-Year Difference in PF per 100,000 People (Assignee, Citation Weighted)	18,846	4.02	50.09	5.71
5-Year Difference in PF per 100,000 People (Inventor)	18,846	8.55	46.93	16.99
5-Year Difference in PF per 100,000 People (Inventor, Citation Weighted)	18,846	8.02	72.53	16.12
Wages				
5-Year Difference in Average Annual Wage	21,977	18.93	56.52	25.80
10-Year Difference in Avg. Annual Wage of Native Non-Movers Aged 25+ (NNM)	6,274	15.00	30.81	37.84
10-Year Difference in Avg. Annual Wage of NNM with Less than High School	6,274	-6.36	36.51	41.75
10-Year Difference in Avg. Annual Wage of NNM with High School	6,274	-1.90	29.86	42.36
10-Year Difference in Avg. Annual Wage of NNM with Some College	6,274	7.54	32.60	43.81
10-Year Difference in Avg. Annual Wage of NNM with B.A.	6,274	22.46	48.31	58.26
10-Year Difference in Avg. Annual Wage of NNM with Graduate School	6,274	46.97	74.06	96.64
Immigration and Education				
Immigration$_{d,t}$ (Age 25+)	21,987	0.80	6.91	0.11
Average Years College$_{d,t}$ (Age 25+)	21,987	1.50	1.41	1.82
Average Years Education$_{d,t}$ (Age 25+)	21,987	10.88	3.65	4.59
Spillovers				
Immigration$_{s(d),t}$	21,987	114.21	216.16	84.90
Neighbors' Immigration$_{n(d),t}$ (Inverse Distance Weight)	21,987	1.15	0.78	0.65
Immigration$_{100km(d),t}$ (other counties within 100km)	21,987	18.58	64.65	9.21
Immigration$_{250km(d),t}$ (other counties within 250km)	21,987	74.96	133.50	67.60
Immigration$_{500km(d),t}$ (other counties within 500km)	21,987	123.10	149.52	143.69

Notes: This table displays the number of observations, mean, standard deviation, and interquartile range for all outcome variables considered, as well as the variables for immigration and the immigration instrument. The first section of the table contains summary statistics for immigration (here we focus only on non-European migration) and population growth in 1,000s of people. The second section lists summary statistics for patenting and differences in patenting per 100,000 people. The third section reports summary statistics for wages ($100). Finally, the fourth and fifth section provide summary statistics on the immigration variables used in the education and spillovers analyses, respectively. Variables for immigration, population growth, and education are all for five-year periods, as are the differenced outcomes except in the case of differences in average annual wage for natives and native non-movers, which are over 10-year periods.

Table 2: Regressions of Immigration on Push-Pull Instruments at the Country-County Level

	$\text{Immigration}^t_{o,d}$				
	(1)	(2)	(3)	(4)	(5)
$\hat{A}_{o,d,1975} \times \tilde{I}_{o,-r(d),1980}$	0.0036***	0.0036***	0.0035***	0.0035***	0.0035***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,1980} \times \tilde{I}_{o,-r(d),1985}$	0.0016***	0.0016***	0.0016***	0.0016***	0.0016***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,1985} \times \tilde{I}_{o,-r(d),1990}$	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,1990} \times \tilde{I}_{o,-r(d),1995}$	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,1995} \times \tilde{I}_{o,-r(d),2000}$	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,2000} \times \tilde{I}_{o,-r(d),2005}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,2005} \times \tilde{I}_{o,-r(d),2010}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$I_{Euro,d,t}$				0.0109***	
				(0.0031)	
$I^t_{o,-r(d)} \frac{I_{Euro,d,t}}{I^{Euro,\cdot,t}}$					0.3913**
					(0.1558)
N	3,583,881	3,583,881	3,583,881	3,583,881	3,583,881
R^2	0.656	0.657	0.709	0.709	0.709
Distance	No	Yes	Yes	Yes	Yes
Latitude Dis.	No	Yes	Yes	Yes	Yes
Region-Country FE	No	No	Yes	Yes	Yes
County-Continent FE	No	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Concurrent European Immigration	No	No	No	Yes	No
Contemporaneous Push-Pull	No	No	No	No	Yes

Notes: This table reports coefficient estimates for step 2 of our instrument construction, shown in equation (4), at the country-county level. Interpretation: in column (1), $Immigration^{1980}_{o,d}$ loads on $\hat{A}_{o,d,1975} \times \tilde{I}_{o,d,1980}$ with a coefficient 0.0036 while $Immigration_{o,d,1985}$ loads on $\hat{A}_{o,d,1980} \times \tilde{I}_{o,d,1985}$ with a coefficient 0.0016. Moving from column 1 to column 3 we introduce controls for distance and latitude distance and then fixed effects into the regression specification. Column 4 adds contemporaneous European migration as a control while column 5 instead introduces the contemporaneous push-economic pull factor for non-European migration. Standard errors are clustered by country for all specifications and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: County-Level Panel Regressions of Difference in Patenting on Immigration

	Δ^{5yr} Patent Flows Per Capita			IHS(Patent Flows Per Capita)
	(1)	(2)	(3)	(4)
Panel A: OLS				
$\text{Immigration}_{d,t}$	0.200**	0.194**	0.309	
	(0.096)	(0.096)	(0.197)	
$\text{IHS}(\text{Immigration}_{d,t})$				1.751***
				(0.140)
N	18,846	18,840	18,846	21,987
R^2	0.030	0.053	0.190	0.577
Panel B: IV				
$\text{Immigration}_{d,t}$	0.122***	0.115**	0.181**	
	(0.045)	(0.045)	(0.087)	
$\text{IHS}(\text{Immigration}_{d,t})$				1.652***
				(0.150)
N	18,846	18,840	18,846	21,987
First Stage F-Stat	911	807	85	94
AR Wald F-Test p-value	0.014	0.021	0.013	0.000
Panel C: First Stage	Immigration_d^t			$\text{IHS}(\text{Immigration}_d^t)$
Immigration Shock ($\hat{I}_{d,t}$)	2.119***	2.124***	1.610***	
	(0.070)	(0.075)	(0.175)	
$\text{IHS}(\hat{I}_{d,t})$				0.792***
				(0.081)
N	18,846	18,840	18,846	21,987
R^2	0.762	0.766	0.956	0.541
Geography FE	State	State	County	State
Time FE	Yes	Yes	Yes	Yes
State-Time FE	No	Yes	No	No

Notes: Panels A and B of this table reports the OLS and IV results, respectively, of the estimation of equation (1) where the dependent variable is the change in patenting per 100,000 people (population is based on baseline 1970 levels) in county d in the five-year period ending in t and the endogenous variable is non-European immigration (1,000s) in d and period t in columns 1 to 3; column 4 reports results for a comparable regression of the inverse-hyperbolic sine (IHS) of patenting per 100,000 people on the IHS of non-European immigration (1,000s). Panel C reports the results for step 3 of instrument construction, or the coefficient estimates for the first-stage specification for non-European immigration (1,000s) for the instrument described in equation (5). The table includes the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each of the IV specifications. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Immigration and Wages

	Δ^{5yr} Wages		Δ^{10yr} Wages					
	Average Annual Wage		*All Native Non-Movers*	*Less than High School*	*High School*	*1 to 3 Years of College*	*4 Years of College*	*5+ Years of College*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigration$_{d,t}$	0.149***	0.217**	0.108***	-0.007	0.017***	0.029**	0.085***	0.247***
	(0.030)	(0.098)	(0.034)	(0.007)	(0.005)	(0.011)	(0.025)	(0.085)
N	21,977	21,976	6,274	6,274	6,274	6,274	6,274	6,274
First Stage F-Stat	903	37	936	936	936	936	936	936
AR Wald F-Test p-value	0.000	0.039	0.006	0.323	0.001	0.021	0.003	0.010
Geography FE	State	County	State	State	State	State	State	State
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of our IV specification, described in equation (1), for each of our dependent variables with non-European immigration for those aged 25+ (1,000s) to d in t as the endogenous variable. Column 1 reports the results of our IV regression where the dependent variable is the change in the average annual real wage ($100s, at 2010 prices) over the five-year period ending in t. Column 2 repeats the specification of column 1 but adds county fixed effects. Columns 3 through 8 report results where the dependent variable is the change in the average annual real wage ($100s, at 2010 prices) for native non-movers (those with birthplace listed as a US state or Washington DC who have not moved in the last 5 years) over the 10-year period ending in t on instrumented non-European immigration for the 10-year period ending in t. Column 3 relies on wage data for all native non-movers aged 25 and older while columns 4 through 8 further limit the sample of wage data to native non-movers aged 25 and older with education levels of less than high school, high school, 1 to 3 years of college, 4 years of college, and at least 5 years of college, respectively. We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Education Analysis

	(1)	(2)	(3)	(4)	(5)
Panel A			Δ^{5yr} Patent Flows Per Capita		
Immigration$_{d,t}$	0.212**	0.254***	0.584	0.514***	
	(0.081)	(0.082)	(0.356)	(0.128)	
Average Years Education$_{d,t}$ × Immigration$_{d,t}$		0.281***	0.280**		
		(0.094)	(0.128)		
Average Years College$_{d,t}$ × Immigration$_{d,t}$				1.076***	
				(0.283)	
$\mathbf{1}$\{Low Avg. Years Education\} × Immigration$_{d,t}$					-1.671
					(5.620)
$\mathbf{1}$\{Medium Avg. Years Education\} × Immigration$_{d,t}$					0.105*
					(0.062)
$\mathbf{1}$\{High Avg. Years Education\} × Immigration$_{d,t}$					1.705**
					(0.830)
N	18,846	18,846	18,846	18,846	18,846
Montiel-Pflueger Effective F-Stat	39	38; 13	18; 15	19; 5	4; 37; 3
AR Wald F-Test p-value	0.000	0.000	0.000	0.000	0.000
Panel B			Δ^{5yr} Wages		
Immigration$_{d,t}$	0.243**	0.298***	0.761*	0.424***	
	(0.095)	(0.058)	(0.385)	(0.093)	
Average Years Education$_{d,t}$ × Immigration$_{d,t}$		0.251***	0.238**		
		(0.055)	(0.097)		
Average Years College$_{d,t}$ × Immigration$_{d,t}$				0.640***	
				(0.101)	
$\mathbf{1}$\{Low Avg. Years Education\} × Immigration$_{d,t}$					-0.264
					(0.259)
$\mathbf{1}$\{Medium Avg. Years Education\} × Immigration$_{d,t}$					0.183***
					(0.064)
$\mathbf{1}$\{High Avg. Years Education\} × Immigration$_{d,t}$					1.637***
					(0.360)
N	21,977	21,977	21,976	21,977	21,977
Montiel-Pflueger Effective F-Stat	42	39; 16	15; 18	19; 5	41; 29; 3
AR Wald F-Test p-value	0.000	0.000	0.000	0.000	0.000
Geogrpahy FE	State	State	County	State	State
Time FE	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of our IV specification (1) for the change in patenting per 100,000 people (population is based on baseline 1970 levels) in Panel A and the 5-year difference in county-level average real annual wages ($100s, at 2010 prices) in Panel B. Column 1 repeats our main specification but adjusting the migrant pool to those aged 25+ (1,000s). Columns 2 and 3 then add a second endogenous variable for the interaction of immigration with the (demeaned) average years of education of the migrants arriving in the destination county, whereas column 4 adds (demeaned) average years of college education of those migrants. Repeating the regression in column 2 of the second panel for the 10-year difference in average annual wages ($100s, at 2010 prices) of native non-movers (US-born working individuals who have not moved outside of the county within the past 5 years) on 10-year migration and corresponding education results in coefficients of 0.249 (0.054) and 0.138 (0.036) on immigration and average years of education times immigration, respectively. Column 5 uses as endogenous variables adult immigration interacted with indicators for the terciles of average years of education of migrants across counties in period t. In all specifications, for instrumentation, we exploit the fact that in our initial instrument construction we created quasi-exogenous immigration shocks for each origin country-o × destination county-d pair in each time period t; each specification utilizes the predicted immigration shocks for each of the the top 20 origin nations as a joint set of instruments. For each regression we report the Montiel Olea and Pflueger (2013) effective F-statistic. In regressions with multiple endogenous variables we use the orthogonalizaiton method described in Angrist and Pischke (2009, p. 217-218). See the main text for details. We report the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Parameters and Model Fit

Panel A: Moments	Data	Model
IV coeff., patenting$_{d,t}$ on immigration $I_{d,t}$	1.6519	1.6410
	(0.1500)	
Std. deviation, o immigration $I_{o,t}$	0.4061	0.3975
	(0.0284)	
Std. deviation d immigration $I_{d,t}$	0.1794	0.1655
	(0.0110)	
Std. deviation, o-d immigration $I_{o,d,t}$	0.0716	0.1138
	(0.0117)	
Autocorrelation, output per capita $Y_{d,t}/L_{d,t}$	0.9611	0.9646
	(0.0057)	
Autocorrelation, patenting$_{d,t}$	0.9309	0.8925
	(0.0065)	
Panel B: Estimated Parameters	**Symbol**	**Value**
Elasticity, patenting to labor	γ	0.7807
		(0.0857)
Autocorrelation, county TFP	ρ	0.8631
		(0.0230)
Std. deviation, county TFP shocks	σ_ϵ	0.0203
		(0.0090)
Std. deviation, immigration push shocks	σ_ν	0.5951
		(0.0793)
Std. deviation, bilateral immigration shocks	σ_τ	0.5200
		(0.0707)

Notes: The top Panel A reports targeted data moments vs simulated model moments. The bottom Panel B reports the estimated parameters. The standard errors, in parentheses beneath moments and estimates, are clustered by state.

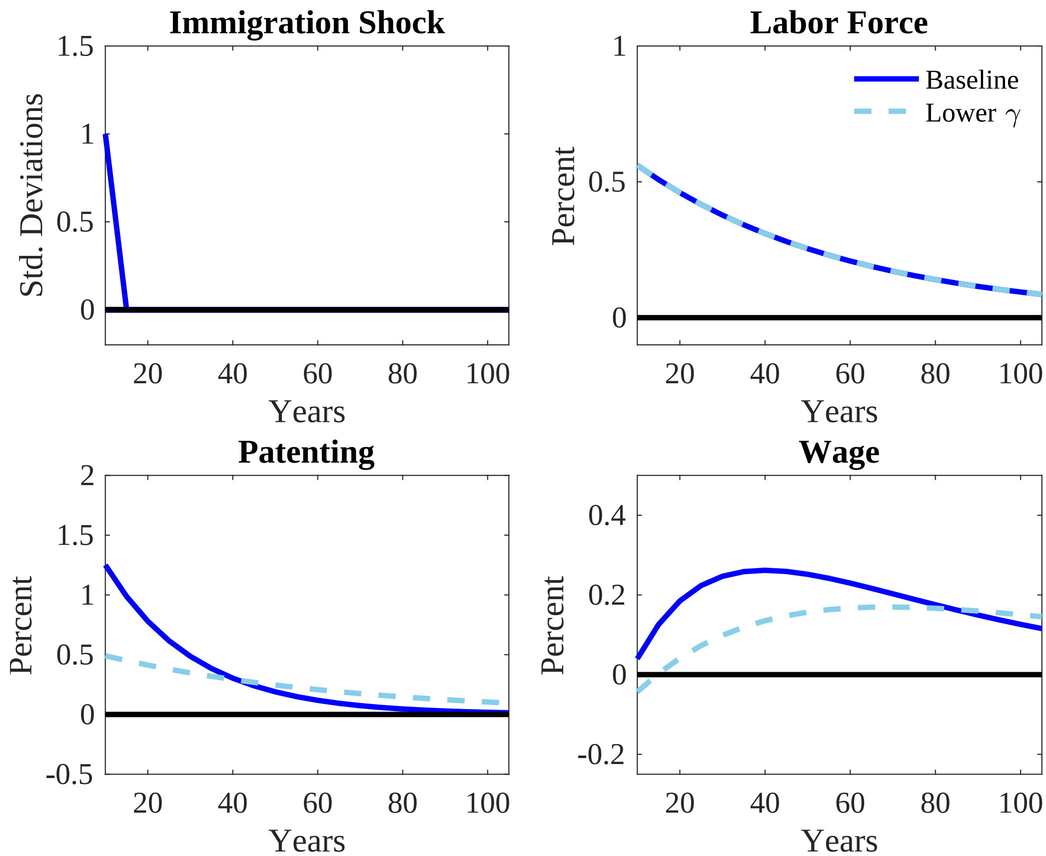
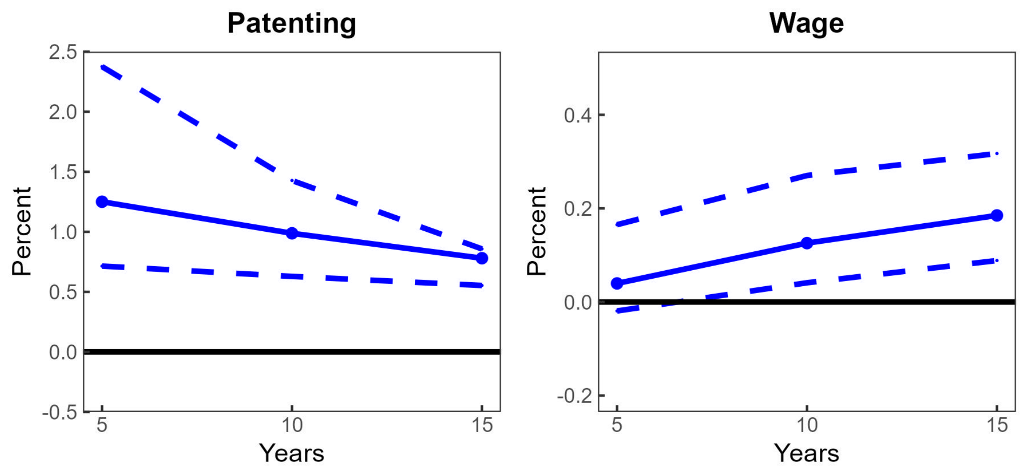


Figure 1: The Impact of an Immigration Shock

Notes: The figure plots impulse response functions to a one-standard deviation immigration shock in period 1. The top left plots the immigration shock $\nu_{o,t}$. The top right plots the labor force $l_{d,t}$. The bottom left panel plots patenting $n_{d,t}$. The bottom right panel plots the response of the wage $w_{d,t}$. The immigration shock is from a single origin o, and the responses of the labor force, patenting, and the wage are local responses for a county d. The labor force, patenting, and wage responses are in percentage point deviations from the balanced growth path. The baseline impacts are in solid blue, while the lighter dashed line lowers the parameter γ from its baseline of 0.781 to 0.5.

Panel A: IRF Responses (Model)



Panel B: IV-Elasticities (Data)

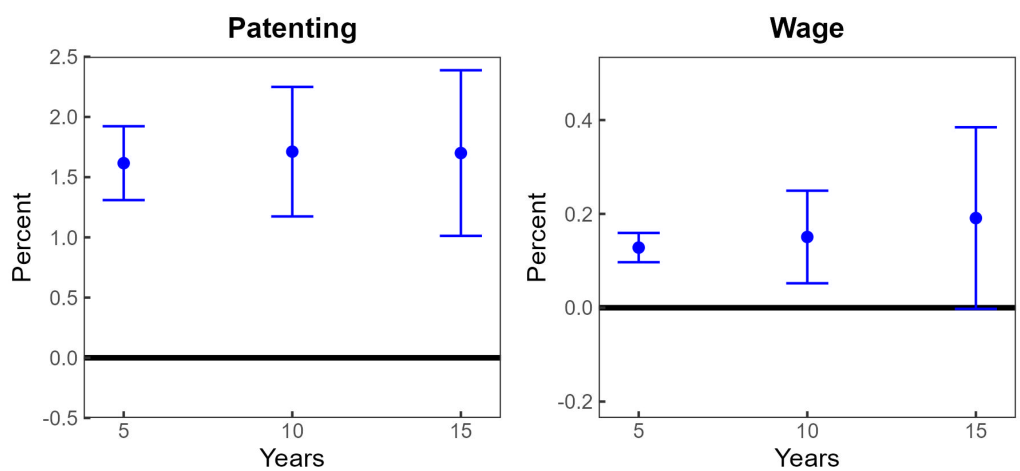


Figure 2: Immigration, Innovation, and Wages: Model versus Data

Notes: Panel A plots model-estimated impulse response functions for patenting (left figure) and wages (right figure) to a one-standard deviation immigration shock in period 1 (with dashed lines representing standard error boundaries associated with γ). Panel B displays the results of estimating equation (1), where the endogenous variable is the inverse hyperbolic (IHS) of non-European immigration (1,000s) to county d at time t and the dependent variable is the IHS of 5-year patent flows per 100,000 people (left figure) or IHS of wages (right figure). The figures plot the coefficient estimate and 95% confidence intervals on the endogenous variable for separate regressions where the outcome is measured in period t, t+1, and t+2 (for the latter two regressions, we include controls for the immigration shock in $t+1$ and the immigration shocks in $t+1$ and $t+2$, respectively).

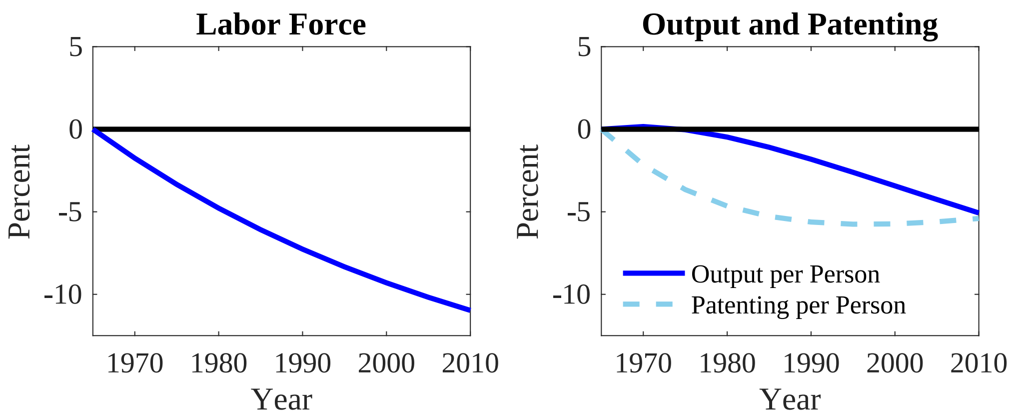


Figure 3: Removing the Post-INA Immigration Increase

Notes: The figure plots the simulated counterfactual impact to US economic outcomes from removing the increase in US population growth due to the foreign born empirically observed after the Immigration and Nationality Act of 1965 (INA). Each panel plots the percent deviation of the indicated outcomes from the path of the economy without removal of the post-INA immigration contributions.

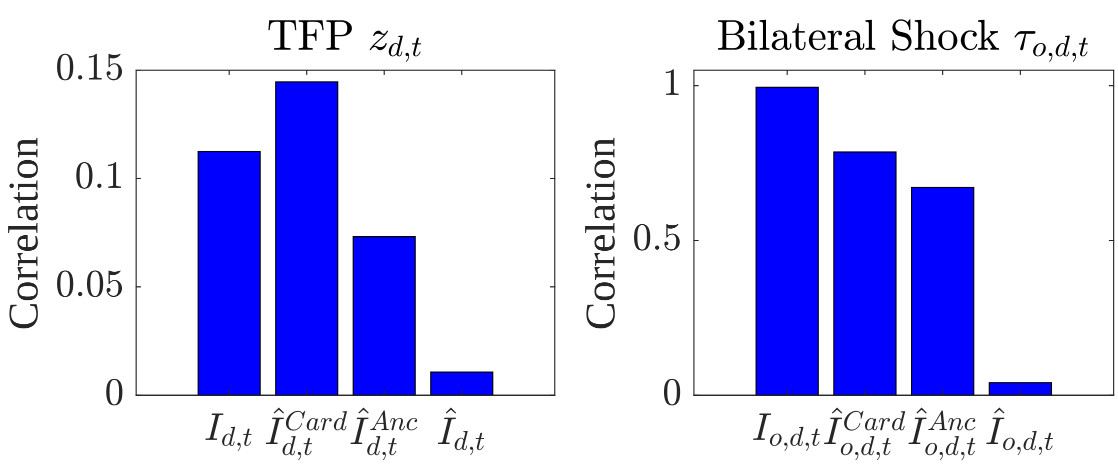


Figure 4: TFP, Bilateral Shocks, and Instrumental Variables

Notes: The figure reports correlations in simulated model data linking observable outcomes of interest to underlying model shock processes. In each panel, the observable data is given by the inverse hyperbolic sine of total immigration I, the Card IV $\hat{I}^{Card}$, a version of our baseline IV with realized rather than predicted ancestry shares $\hat{I}^{Anc}$, and our baseline IV $\hat{I}$. The left panel reports correlations from data aggregated to the destination county d by time t level with the log county-level TFP shock $z_{d,t}$. The right panel reports correlations from data disaggregated to the origin country o by destination county d by time t level with (minus) the bilateral immigration shock -$\tau_{o,d,t}$.

Online Appendix

"Immigration, Innovation, and Growth"

Stephen J. Terry

Thomas Chaney

Konrad B. Burchardi

Lisa Tarquinio

Tarek A. Hassan

A Data Appendix

A.1 Details on the construction of migration and ethnicity data

To construct county-level data on migration, ancestry, and ethnicity, we follow the approach of Burchardi et al. (2019). We utilize data from each available wave of data from 1880 to 2010 from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2018-2020). Specifically, we use the 10% sample of the 1880 Census, the 5% sample of the 1900 Census, the 1% sample of the 1910 Census, the 1% sample of the 1920 Census, the 5% sample of the 1930 Census, 1% Form 1 Metro sample of the 1970 Census, 5% State sample of the 1980 Census, 5% State sample of the 1990 Census, 5% sample of the 2000 Census, and the American Community Service 5-Year sample of the 2010 Census. The following section summarizes this approach, highlighting any difference in data construction made in this paper.

Construction of post-1880 immigration flows

We start the construction of our immigration variable by identifying the number of individuals located in a given US geography d at the time of each census who immigrated to the US since the prior census and were born in a historic origin country o (based on the detailed birthplace variable). For each census wave, we then separate this immigration count into (roughly) five-year periods based on the year in which each migrant arrived to the US. For the 1970, 1980, and 1990 censuses, the exact year of arrival for immigrants is not provided, and instead the year of arrival is provided in bins (e.g., a person who arrived in 1964 has a year of arrival of 1960-1964). For these years, we use as our five-year periods the bins that are reported in each census: 1925-34, 1935-44, 1945-49, 1950-54, 1955-59, 1960-64, 1965-70, 1970-74, 1975-80, 1980-84, and 1985-90. We then follow the approach outlined in Burchardi et al. (2019) to transform foreign origin countries, given as birthplaces, to 1990 foreign countries and non-1990 counties and county groups into 1990 counties. Because some foreign birthplaces do not refer to any modern (1990) country, we use population-based weights for transitioning birthplaces to countries (for more details on the weighting scheme, see Burchardi et al. (2019)). We define adult immigrants as those aged 25 years and older at the time of the census.

Construction of pre-1880 immigration stock

From the 1880 census, we count all individuals who were born in a foreign origin country o and reside in a historic US geography d, regardless of the date of arrival to the US. We then add to this count all individuals residing in d who were born in the US but whose parents were born in origin country o (if an individual's parents were born in different countries, the individual is assigned a count of one half for each parent's origin country o). We then transform the given birthplace to 1990 foreign countries and the pre-1880 US geography to 1990 US counties following the transition method outlined in Burchardi et al. (2019).

Construction of ancestry stock

For the years 1980, 1990, 2000, and 2010, we take from the respective census all individuals in a US county or county group that list as their primary ancestry a foreign nationality or area. We then estimate the ancestry stock in each midyear (1975, 1985, 1995, and 2005) by taking the individuals identified in each census year as belonging to a given ancestry and removing all individuals who either were born or migrated to the US after the midyear. Ideally, we would also remove all individuals who moved to the county after the midyear, but data is not available for all census years; thus, for consistency, we do not remove these individuals. Again, we follow Burchardi et al. (2019) in transforming ancestries to 1990 countries and US geographies to 1990 US counties. As with the data on foreign birthplaces, some ancestries do not correspond directly to a modern (1990) country; again, we follow the weighting scheme outlined in Burchardi et al. (2019) for transitioning stated ancestries to 1990 foreign countries.

Construction of education data for migrants

For the five-year migration periods from 1975 to 2010, whose construction is previously described, we also identify the total number of years of education for each set of immigrants. Specifically, we take the set of individuals that make up each five-year immigration flow and limit to those individuals who are aged 25 years or older at the time of each respective census. For each 1990 US county d, we then sum the number of years each individual is reported to have over all immigrants in this set, assigning the midpoint when a range of years of education is provided instead of an exact number of years. We then generate the average years of education for immigrants to county d in each period t and demean these values. Finally, we take the demeaned average years of education and multiply by the count of immigrants aged 25 or older to generate the (demeaned) total years of education. We construct this variable for total years of education as well as for years of college education.

We also utilize information on education from the census to construct county-level demographic controls for the share of the county's population that has a specified level of education in a baseline year, 1970. Using data from the 1970 census, we calculate the share of all individuals, regardless of birthplace, residing in a historic US county d who report having at least a Grade 12 education (share of high-school educated) and those who report having at least four years of college education (share of college educated). These values are then transformed from 1970 US counties to 1990 US counties, again using the transition matrices described by Burchardi et al. (2019).

A.2 Construction of population data

For the period 1970 to 2010, we collect county-level population data in each census year and intercensal year. The population counts for 2010 were taken directly from the US Census Bureau (the American Community Survey 5-year estimates). All other population counts are taken from the NBER (2018)'s Census U.S. Intercensal County Population Data, 1970-2014. For each period, data are transformed from the given US counties to 1990 US counties using the transition matrices described by Burchardi et al. (2019).

A.3 Construction of patenting data

We utilize data on corporate utility patents with a US assignee from the the US Patent and Trademark Office (USPTO) microdata for the period 1975 to 2010 (USPTO, Accessed: Mar. 28-29, 2022). We translate the location of patents from assignee (or inventor) location to 1990 US counties by mapping the latitude and longitude coordinates onto a shapefile of 1990 counties (obtained from IPUMS NHGIS (Manson et al., 2023)) to estimate the number of patents granted to assignees in each county and year. For our main measure of patenting, we utilize unweighted patent counts with locations based on assignee, but we also consider location based on inventors and weighted patent counts as in Hall et al. (2001). We then construct a variable for the total number of patents filed in each five-year period ending in t, for each measure of patenting, and divide by the 1970 population (100,000 people) to get "per-capita patenting" in t. We then winsorize the variables at the 1% and 99% levels. The main patenting outcome variable is then the difference in this per-capita-patenting variable between $t-1$ and t.

For the inventor-based measure of patenting, we also identify the subset of patents for which all inventors are designated as natives (as opposed to immigrants). Because we do not have information on inventor citizenship, we define native inventors as those whose first patent in the USPTO dataset is filed in the US. This definition of *native inventors* may include patents filed by foreign-born inventors if they first file a patent after moving to the US. Therefore, we also construct the count of of patent flows for *native inventors with a prior US patent* that further restricts the sample to patents filed in period t by only native inventors who have filed another patent in the US prior to t. While this latter definition does not account for individuals who are long-term foreign-born residents in the US that file their first patent at least 5 years after moving, it does remove patents that may have been filed by recent immigrants (as well as removing all patents by first-time native-born inventors or inventors whose previous patents are not contained in the USPTO dataset). Finally, we apply a further restriction limiting the set of patents to those for which all inventors have filed a patent prior to the current period in the same US county (or at least one of the same counties if the inventor filed in multiple locations in period t).

A.4 Construction of native wages data

We construct variables for native wages in each census year from 1980 to 2000 using data from the 1980 5% State sample, 1990 5% State sample, and 2000 5% Census sample (Ruggles et al., 2018-2020). In each year, we limit the sample to the pre-tax wage and salary income (incwage) for individuals aged 25 and older who were born in the US and are employed (empstat is equal to 1), referred to here as natives. We then further limit the sample to natives who report that they lived in the same county five years prior to the census year to identify wages of native non-movers. Additionally, we subset the data based on the education level of the individuals to estimate the wages of native non-movers with education levels of: less than high school, high school, some college (1-3 years), 4 years of college, and 5 or more years of college. We use the Consumer Price Index provided in IPUMS USA (CPI99) to adjust wages to a common dollar year, 1999. We then follow the same method as that used in Burchardi et al. (2019) to transform wages for county groups into 1990 US counties. Finally, we determine average wages in each county using the person weight (PERWT) for the selected sample and generate a variable for wage growth in each county that is the 10-year difference in average annual wages for native non-movers.

A.5 Construction of business dynamism data

In this section, we explain the construction of variables used to measure business dynamism. In each case, we take the five-year difference in the dynamism or wage variable.

Wages. The county-level average annual wage for every five years from 1975 to 2010 is taken from the Quarterly Census of Employment and Wages (BLS, 2018). The data for each period are then transformed from the US counties for that period to 1990 US counties using the transition matrices developed in Burchardi et al. (2019) and then converted to 2010 US dollars using the Personal Consumption Expenditures Price Index from the Bureau of Economic Analysis (BEA, 2018). We generate this county-level average annual wage for all industries as well as manufacturing (SIC 20-39 and NAICS 31-33) and services (SIC 60-67 and NAICS 52-53).

Growth Rate Skewness. The growth rate skewness variable for 2010 US counties for each five years from 1995 to 2010 is estimated using data from the Longitudinal Business Database (US Census Bureau, 2018b). We compute the Kelly Skewness of employment growth rates across 4-digit sectors, and then transition this measure from 2010 to 1990 US counties.

Job Creation and Destruction Rates. Job creation and destruction data are taken from the Business Dynamics Statistics (US Census Bureau, 2018a) for metropolitan statistical areas (MSAs) and transitioned to 1990 US counties based on weights derived from 1990 population data.

A.6 Construction of local output data

Local output data come from the BEA (2021)'s county-level GDP estimates for five-year periods for the available window from 2001 to 2019. These estimates are used to calculate the autocorrelation of county-level output per capita, a target moment of the structural model estimation.

A.7 Additional Tables and Figures

Appendix Table 1: Assignment of States to Census Divisions (US Census Bureau, 2013)

Census Region	State Names
New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
Middle Atlantic	New Jersey, New York, Pennsylvania
East North Central	Illinois, Indiana, Michigan, Ohio, Wisconsin
West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
South Atlantic	Delaware, District Of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia
East South Central	Alabama, Kentucky, Mississippi, Tennessee
West South Central	Arkansas, Louisiana, Oklahoma, Texas
Mountain	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
Pacific	Alaska, California, Hawaii, Oregon, Washington

Appendix Table 2: Robustness - Alternative Share-Based Instruments and Rejection Rates

	Δ^{5yr} Patent Flows Per Capita		
Specification:	*Predicted Ancestry Shares (Baseline)*	*Realized Immigration Shares (Card, 2001)*	*Realized Ancestry Shares*
	(1)	(2)	(3)
Adão et al. (2019) First Stage False Rejection Rate (%)	3.8	27.4 *Overreject*	24.5 *Overreject*
Immigration$_{d,t}$	0.202**	0.161	0.163
	(0.084)	(*0.075*)	(*0.071*)
N	18846	18846	18846
First Stage F-Stat	656	695	361
Instrument Functional Form:			
Instrumented Ancestry	Yes	No	No
Push Factor Leave-Out	Yes	No	No
Controls:			
Geography FE	State	State	State
Time FE	Yes	Yes	Yes

Notes: This table displays the results of estimating equation (1), where the dependent variable is the change in patenting per 100,000 people (population is based on baseline 1970 levels) and the endogenous variable is non-European immigration (1,000s) to county d at time t. Column 1 uses our baseline instrument but with predicted ancestry shares, as opposed to predicted ancestry in levels. Column 2 is an instrument based on Card (2001) that utilizes realized immigration shares. Column 3 replaces the realized immigration shares in column 2 with realized ancestry shares. We report the first-stage F-statistic on the excluded instrument for each specification. For each instrument, we report the false rejection rate in the first-stage regression for a robustness test that follows the method proposed by Adão et al. (2019). See Appendix Table 3 for details. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 3: Results from Placebo Analysis Based on Adão et al (2019)

	(1)	(2)	(3)	(4)
	Coefficient (Mean)	Coefficient (St. Dev.)	Standard Error (Median)	Rejection Rate (%)
Panel A: Realized Immigration Shares (Card, 2001)				
First Stage	-0.0038	0.0703	0.0377	24.5
Reduced Form	-0.0003	0.0182	0.0117	15.1
Panel B: Realized Ancestry Shares				
First Stage	-0.0040	0.0791	0.0398	27.4
Reduced Form	-0.0004	0.0200	0.0128	14.9
Panel C: Predicted Ancestry Shares (Baseline Instrument)				
First Stage	-0.0016	0.0397	0.0249	3.8
Reduced Form	0.0004	0.0946	0.0801	9.1

Notes: Following Adão et al. (2019), we randomly generate immigration shocks (for each $\{o, r, t\}$ country-region-time triplet), and construct placebo instruments by interacting these random shocks with realized immigration shares (as in Card (2001)), realized ancestry shares, and our predicted baseline ancestry shares (as in the ancestry-share version of our baseline instrument). We then run 1,000 placebo regressions of the endogenous immigration variabale on the placebo variables for the Card (2001) instrument (Panel A), the Card-style instrument that uses ancestry shares (Panel B), and our ancestry-share instrument (Panel C); we also run the comparable reduced-form regressions where the dependent variable is our primary measure of patenting, the five-year difference in patenting flows per 100,000 people. Column 1 reports the mean value of the coefficient over all placebo regressions, whereas column 2 reports the standard deviation. Column 3 then reports the median standard error for the coefficient of interest over all placebo regressions, and column 4 reports the fraction of placebo regressions for which we reject the null hypothesis of no effect at the 5% statistical significance threshold. As shown, the traditional shift-share instrument suffers from the over-rejection identified in Adão et al. (2019) with false rejection rates of 24.6% in the first stage and 13.6% in the reduced-form specification. The ancestry-share version of our baseline instrument has false rejection rates of 4.7% (first stage) and 8.4% (reduced form). The latter is similar to the false rejection rates reported in Adão et al. (2019) when using their proposed standard error correction (labelled "AKM").

Appendix Table 4: Robustness - County Level vs. State Level Regressions

	Δ^{5yr} Patent Flows Per Capita			
	County Level		*State Level*	
	Predicted Ancestry Shares	*Realized Ancestry Shares*	*Predicted Ancestry Shares*	*Realized Ancestry Shares*
	(1)	(2)	(3)	(4)
Immigration$_{d,t}$	0.2021**	0.1626**	0.0005***	0.0005***
	(0.0841)	(0.0713)	(0.0002)	(0.0001)
N	18,846	18,846	306	306
First Stage F-Stat	656	361	97	1,154
Geography FE	State	State	Division	Division
Time FE	Yes	Yes	Yes	Yes

Notes: This table displays the results of estimating equation (1), where the dependent variable is the change in patenting per 100,000 people (population is based on baseline 1970 levels) and the endogenous variable is non-European immigration (1,000s) to d in t. Columns 1 and 3 use our baseline instrument but with predicted ancestry shares, as opposed to predicted ancestry in levels, and columns 2 and 4 use the comparable instrument but with realized ancestry shares. Columns 1 and 2 report a county level analysis while columns 3 and 4 repeat each regression at the state level. We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 5: Robustness - Alternative Instruments for Immigration

	Alternative Instrument Constructions			
	Leave-Out Correlated Counties	*Leave-Out Own Continent*	*Ancestry in 1975 only*	*Stop Push-Pull in 1960*
	(1)	(2)	(3)	(4)
Panel A	Δ^{5yr} Patent Flows Per Capita			
Immigration$_{d,t}$	0.096***	0.122***	0.111***	0.101***
	(0.035)	(0.045)	(0.040)	(0.038)
N	18,846	18,846	18,846	18,846
First Stage F-Stat	127	828	1,171	1,750
AR Wald F-Test p-value	0.002	0.016	0.011	0.012
Panel B	IHS of Patent Flows Per Capita			
IHS(Immigration$_{d,t}$)	1.672***	1.649***	1.644***	1.725***
	(0.178)	(0.159)	(0.148)	(0.161)
N	21,987	21,987	21,987	21,987
First Stage F-Stat	63	56	109	54
AR Wald F-Test p-value	0.000	0.000	0.000	0.000
Geography FE	State	State	State	State
Time FE	Yes	Yes	Yes	Yes

Notes: Panel A of this table displays the results of estimating equation (1), where the dependent variable is the change in patenting per 100,000 people (population is based on baseline 1970 levels) and the endogenous variable is non-European immigration (1,000s) to d in t; Panel B reports the comparable regression where the dependent variable is the IHS of patenting per 100,000 people and the endogenous variable is the IHS of non-European immigration (1,000s). Column 1 takes the sum over push-pull interaction up to the year 1960 only in Step 1 to create an instrument for ancestry. Column 2 replaces predicted ancestry in $t-1$ with predicted ancestry in 1975 for all periods. Column 3 uses an alternative leave-out strategy in Step 1: the push factor excludes all destination counties whose overall time series of immigration flows are correlated with those of d (as opposed to excluding counties in the same census division ($r(d)$) as d). Column 4 replaces the economic pull factor in Step 1 with the share of all migrants who settle in d but excluding migrants from the same continent as o (instead of using only European migrants). We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 6: Robustness - First Stage Controlling for Lagged Immigration Shocks

	$\text{Immigration}_{d,t}$	
	(1)	(2)
$\text{ImmigrationShock}_{d,t}$	1.580***	1.623***
	(0.196)	(0.222)
$\text{ImmigrationShock}_{d,t-1}$		-0.064
		(0.232)
N	21,987	18,846
R^2	0.495	0.572
Geography FE	County	County
Time FE	Yes	Yes

Notes: This table reports the results for the coefficient estimates for the first-stage specification for non-European immigration (1,000s) for the instrument described in equation (5). Column 1 provides our baseline first stage regression with county and time fixed effects while column 2 adds the lagged immigration shock as a control. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 7: Panel Regression of 5-Year Difference in Patenting per 100,000 People on Immigration using Alternative Patent Counts

	Δ^{5yr} Patent Flows Per Capita			
	Assignee (Unweighted)	*Assignee (Cite Weight)*	*Inventors (Unweighted)*	*Inventors (Cite Weight)*
	(1)	(2)	(3)	(4)
Immigration$_{d,t}$	0.122***	0.150***	0.085**	0.137***
	(0.045)	(0.050)	(0.037)	(0.045)
N	18,846	18,846	18,846	18,846
First Stage F-Stat	911	911	911	911
AR Wald F-Test p-value	0.014	0.008	0.037	0.007
Geography FE	State	State	State	State
Time FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of our second-stage specification, described in equation (1), for the change in patenting per 100,000 people (population is based on baseline 1970 levels) with non-European immigration (1,000s) to d in t as the endogenous variable. Column 1 repeats our main specification where patent location is based on assignees and raw patent counts are used. Column 2 also uses the assignee for patent location but uses citation-weighted patent counts. Columns 3 and 4 then provide results when inventors are used for identifying patent location where patent counts are unweighted and citation-weighted, respectively. We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 8: Permutation Tests for Main Specification

	(1)	(2)	(3)	(4)
	Coefficient (Mean)	(St. Dev.)	Standard Error (Mean)	RHS Rejection Rate (%)
Panel A: First Stage				
Placebo 1	0.0007	0.018	0.008	0.40
Placebo 2	-0.0006	0.013	0.008	0.10
Placebo 3	-0.0127	0.031	0.021	1.90
Panel B: Reduced Form				
Placebo 1	0.0035	0.054	0.041	1.30
Placebo 2	0.0009	0.049	0.037	1.50
Placebo 3	0.0034	0.069	0.045	5.20

Notes: This table reports the results of three different placebo tests on our standard specification, corresponding to column 2 of Table 3. For each of the placebo tests, we randomly reassign the instrument across observations: in the first version, we randomly reassign within the entire sample (Placebo 1); in the second version, we randomly reassign within the same period t (Placebo 2); and in the third version, we reassign within the same period t and census division $r(d)$ (Placebo 3). For each version, we perform 1000 placebo runs. We present summary statistics on the first stage (Panel A) and reduced form (Panel B) coefficients of interest across placebo runs. Columns 1 and 2 report the average and standard deviation for the coefficient of interest, column 3 reports the mean standard errors, and columns 4 reports the percentage of runs for which we reject that the coefficient of interest is different from 0 at the 5% level on the right-hand side. The standard errors are clustered by state in our standard specification and hence all placebo runs.

Appendix Table 9: County-Level Panel Regressions of Difference in Patenting on Population Growth

	Δ^{5yr} Patent Flows Per Capita		
	(1)	(2)	(3)
Panel A: OLS			
Δ Population$_{d,t}$	0.281***	0.279***	0.157*
	(0.086)	(0.087)	(0.079)
N	18,846	18,840	18,846
R^2	0.046	0.068	0.190
Panel B: IV			
Δ Population$_{d,t}$	0.136***	0.130***	0.140**
	(0.044)	(0.045)	(0.069)
N	18,846	18,840	18,846
First Stage F-Stat	110	103	63
AR Wald F-Test p-value	0.014	0.021	0.013
Panel C: First Stage	Δ *Population*$_{d,t}$		
Immigration Shock ($\hat{I}_{d,t}$)	1.897***	1.888***	2.081***
	(0.181)	(0.186)	(0.263)
N	18,846	18,840	18,846
R^2	0.324	0.340	0.804
Geography FE	State	State	County
Time FE	Yes	Yes	Yes
State-Time FE	No	Yes	No

Notes: Panels A and B of this table report the OLS and IV results, respectively, of the estimation of equation (1) where the dependent variable is the change in patenting per 100,000 people (population is based on baseline 1970 levels) in county d in the five-year period ending in t and the endogenous variable is population growth (1,000s) in d and period t. Panel C reports the results for step 3 of instrument construction, or the coefficient estimates for the first-stage specification for population change (1,000s) for the instrument described in equation (5). The table includes the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each of the IV specifications. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 10: Robustness - Additional Controls from Baseline Year (1970)

	Δ^{5yr} Patent Flows Per Capita				
	(1)	(2)	(3)	(4)	(5)
Immigration$_{d,t}$	0.122***	0.125**	0.125***	0.106**	0.090**
	(0.045)	(0.048)	(0.045)	(0.040)	(0.036)
Population Density (1970)		-0.001			
		(0.001)			
Patents per 1,000 People (1975)			-3.377		
			(2.313)		
Share High School Education (1970)				51.754***	
				(10.185)	
Share 4+ Years College (1970)					178.858***
					(25.374)
N	18,846	18,840	18,840	18,846	18,846
First Stage F-Stat	911	2,062	920	945	1,017
AR Wald F-Test p-value	0.014	0.016	0.014	0.018	0.021
Geography FE	State	State	State	State	State
Time FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of our IV specification, described in equation (1), where the dependent variable is the change in patenting per 100,000 people (population is based on baseline 1970 levels) and the endogenous variable is non-European immigration (1,000s) to d in t. Column 1 repeats our main specification, whereas columns 2-5 add as a control county d's population density in 1970, patents filed in 1975 per 1,000 people (1970 population is used to match the dependent variable), share of high school educated, and share of the population with 4+ years of college, respectively. We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 11: Robustness - Alternative Samples

	Δ^{5yr} Patent Flows Per Capita				
	Mexico	*China*	*India*	*Philippines*	*Vietnam*
	(1)	(2)	(3)	(4)	(5)
Panel A: Excluding Given Country					
$\text{Immigration}_{d,t}$	0.091***	0.123***	0.122***	0.122***	0.122***
	(0.028)	(0.046)	(0.045)	(0.044)	(0.045)
N	18,846	18,846	18,846	18,846	18,846
First Stage F-Stat	666	1,576	1,267	1,261	1,179
AR Wald F-Test p-value	0.003	0.015	0.014	0.014	0.014
Panel B: Including Only Given Country					
$\text{Immigration}_{d,t}$	0.125***	0.089***	0.145***	0.140**	0.125*
	(0.047)	(0.028)	(0.039)	(0.054)	(0.069)
N	18,846	18,846	18,846	18,846	18,846
First Stage F-Stat	2,094	535	318	22	2
AR Wald F-Test p-value	0.015	0.003	0.001	0.000	0.148
Geography FE	State	State	State	State	State
Time FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of our IV specification, described in equation (1), run on alternative samples where the dependent variable is the change in patenting per 100,000 people (population is based on baseline 1970 levels) and the endogenous variable is non-European immigration (1,000s) to d in t. In instrument construction, each column either drops migrants from the given country (Panel A) or drops all other migrants except those from the specified country (Panel B) from the sum in equation (5) for each of the five largest sending countries post 1975 (Mexico, China, India, Philippines, and Vietnam). We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification, and note the instrument constructed using only migrants from Vietnam does not significantly predict non-European immigration. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 12: Mechanisms: Patents by Inventor Type

	Δ^{5yr} Patent Flows Per Capita			
	All Inventors	*Domestic Inventors*	*Immigrant Inventors*	*Teams of Domestic & Immigrant Inventors*
	(1)	(2)	(3)	(4)
Immigration$_{d,t}$	0.085**	0.069**	0.003***	0.009**
	(0.037)	(0.030)	(0.001)	(0.004)
N	18,846	18,846	18,846	18,846
First Stage F-Stat	911	911	911	911
AR Wald F-Test p-value	0.037	0.038	0.004	0.027
Geography FE	State	State	State	State
Time FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of our IV specification, described in equation (1), for changes in patenting per 100,000 people with non-European immigration to d in t as the endogenous variable. Column 1 uses our baseline patenting variable but with a patent's county designated based on inventor location (as opposed to assignee location). Column 2 repeats this specification but limits to patents with only domestic inventors, defined as those whose first patent was filed in the US (92% of all patents). Column 3 limits patents in the dependent variable to those with only immigrant inventors, defined as those whose first patent was filed abroad and have at least one patent in the US (1% of all patents). Finally, Column 4 limits patents in the dependent variable to only those with domestic and immigrant inventor teams (4% of all patents). Patents with at least one foreign inventor, defined as those with all patents filed abroad, make up the remaining 3% of all patents. We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 13: Mechanisms: Domestic Non-Mover Innovators

	Δ^{5yr} Patent Flows Per Capita			
	All Inventors	*Only Domestic Inventors*	*Only Domestic Inventors with Prior US Patent*	*Only Domestic Inventors with Prior US Patent* in Same County
	(1)	(2)	(3)	(4)
$\text{Immigration}_{d,t}$	0.085**	0.069**	0.040**	0.033**
	(0.037)	(0.030)	(0.018)	(0.014)
N	18,846	18,846	18,846	18,846
First Stage F-Stat	911	911	911	911
AR Wald F-Test p-value	0.037	0.038	0.037	0.032
Geography FE	State	State	State	State
Time FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of our IV specification, described in equation (1), for changes in patenting per 100,000 people with non-European immigration to d in t as the endogenous variable. Column 1 uses our baseline patenting variable but with a patent's county designated based on inventor location (as opposed to assignee location). Column 2 repeats this specification but limits to patents with only domestic inventors, or inventors whose first patent was filed in the US (92% of all patents). Column 3 further limits patents in the dependent variable to those with only domestic inventors who have filed at least one patent in the US prior to the current period (40% of all patents). Finally, Column 4 further limits patents in the dependent variable to those with only domestic inventors who have filed at least one patent prior to the current period in the same US county or at least one of the same counties in the case that they file in multiple locations in period t (32% of all patents). We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 14: Spillovers Analysis

	(1)	(2)	(3)	(4)
Panel A		Δ^{5yr} Patent Flows Per Capita		
$\text{Immigration}_{d,t}$	0.137***	0.124***	0.076*	0.076
	(0.048)	(0.045)	(0.044)	(0.048)
$\text{Immigration}_{s(d),t}$		0.007***		
		(0.002)		
Neighbors' $\text{Immigration}_{n(d),t}$ (Inverse Distance Weight)			6.916***	
			(2.061)	
$\text{Immigration}_{100km(d),t}$				0.077***
				(0.026)
$\text{Immigration}_{250km(d),t}$				0.005
				(0.005)
$\text{Immigration}_{500km(d),t}$				0.004
				(0.004)
N	18,846	18,846	18,846	18,846
First Stage F-Stat (first coefficient)	876	1,129	2,175	6,065
First Stage F-Stat (second coefficient)		807	162	383
First Stage F-Stat (third coefficient)				150
First Stage F-Stat (fourth coefficient)				66
AR Wald F-Test p-value	0.011	0.000	0.000	0.000
Panel B		Δ^{5yr} Wages		
$\text{Immigration}_{d,t}$	0.178***	0.180***	0.094***	0.105***
	(0.036)	(0.051)	(0.022)	(0.033)
$\text{Immigration}_{s(d),t}$		-0.001		
		(0.014)		
Neighbors' $\text{Immigration}_{n(d),t}$ (Inverse Distance Weight)			9.924***	
			(3.309)	
$\text{Immigration}_{100km(d),t}$				0.104***
				(0.038)
$\text{Immigration}_{250km(d),t}$				-0.012
				(0.020)
$\text{Immigration}_{500km(d),t}$				-0.004
				(0.016)
N	21,977	21,977	21,977	21,977
First Stage F-Stat (first coefficient)	872	881	3,065	7,031
First Stage F-Stat (second coefficient)		840	175	437
First Stage F-Stat (third coefficient)				160
First Stage F-Stat (fourth coefficient)				66
AR Wald F-Test p-value	0.000	0.000	0.000	0.000
Geography FE	Division	Division	Division	Division
Time FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of our IV specification (1) for the change in patenting per 100,000 people (population is based on baseline 1970 levels) (Panel A) and the change in the real average annual wage ($100s, at 2010 prices) (Panel B) with non-European immigration (Panel A) and immigration limited to those aged 25+ (Panel B) (1,000s) to d in t as the endogenous variable. The first column repeats our baseline specification but with census division fixed effects. Column 2 adds as a second endogenous variable: total non-European immigration to the state in which d is located, excluding own-immigration to d, in period t and a comparable instrument. Column 3 adds as a second endogenous variable the inverse-distance-weighted sum of non-European immigration to all counties in the US, excluding own-immigration, and an instrument constructed analogously. Column 4 includes variables, and appropriate instruments, for non-European immigration to counties within 100km (excluding d), 100km to 250km, and 250km to 500km of county d. For each specification we report the first-stage F-statistic(s), utilizing the F-statistic described in Angrist and Pischke (2009, p. 217-218) in the case of multiple endogenous variables. We report the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 15: Spillover Analysis – First Stage

	Column 1	Column 2		Column 3		Column 4			
	Immigration_d^t (1)	$\text{Immigration}_{d,t}$ (2)	$\text{Immigration}_{s(d),t}$ (3)	$\text{Immigration}_{d,t}$ (4)	Neighbors' $\text{Immigration}_{n(d),t}$ (5)	$\text{Immigration}_{d,t}$ (6)	$\text{Immigration}_{100km(d),t}$ (7)	$\text{Immigration}_{250km(d),t}$ (8)	$\text{Immigration}_{500km(d),t}$ (9)
Immigration Shock ($\hat{I}_{d,t}$)	2.130***	2.126***	0.487**	2.093***	0.001	2.094***	-0.379	-0.080	0.345
	(0.072)	(0.072)	(0.232)	(0.055)	(0.002)	(0.058)	(0.257)	(0.264)	(0.450)
State Immigration Shock ($\hat{I}_{s(d),t}$)		0.003	2.778***						
		(0.002)	(0.125)						
Neighbors' Immigration Shock ($\hat{I}_{n(d),t}$)				4.938*	2.388***				
				(2.730)	(0.369)				
Immigration Shock 100km ($\hat{I}_{100km(d),t}$)						0.058	3.404***	-0.071	-1.264
						(0.040)	(0.993)	(0.322)	(0.764)
Immigration Shock 250km ($\hat{I}_{250km(d),t}$)						0.006	-0.047	2.623***	-0.617*
						(0.011)	(0.095)	(0.387)	(0.315)
Immigration Shock 500km ($\hat{I}_{500km(d),t}$)						-0.006	-0.201*	-0.339	2.030***
						(0.007)	(0.120)	(0.232)	(0.263)
N	18,846	18,846	18,846	18,846	18,846	18,846	18,846	18,846	18,846
First Stage F-Stat	876	1,129	807	2,175	162	6,065	383	150	66
Geogrpahy FE	Division	Division	Division	Division	Division	Division	Division	Division	Division
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of the first-stage regressions for the IV regressions shown in Table 14. Column 1 of this table provides the first stage regression for column 1 of Table 14. The first stages for column 2 of Table 14 are shown in columns 2 and 3 of this table while those for column 3 in Table 14 are shown in columns 4 and 5 of this table. Finally, columns 6-9 display the first-stage regressions for column 4 of Table 14. For each specification, we report the first-stage F-statistic for the IV estimation in Table 14, utilizing the F-statistic described in Angrist and Pischke (2009, p. 217-218) in the case of multiple endogenous variables. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 16: Panel Regressions of Inflows of Native Migrants on Non-European Immigration

	Inflows of Internal Migrants	
	All Natives	*Non-Hispanic White Natives*
	(1)	(2)
$\text{Immigration}_{d,t}$	3.675***	2.100***
	(0.616)	(0.406)
N	9,415	9,415
First Stage F-Stat	3,484	3,484
AR Wald F-Test p-value	0.000	0.000
Geography FE	State	State
Time FE	Yes	Yes

Notes: This table reports the results of our second-stage specification, described in equation (1), for the migration of natives (1,000s) into county d in period t (for 1980, 1990, and 2000) with non-European immigration (1,000s) to d in t as the endogenous variable. Note, migrants who moved into county d from a foreign country are excluded. We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 17: Immigration and Economic Dynamism

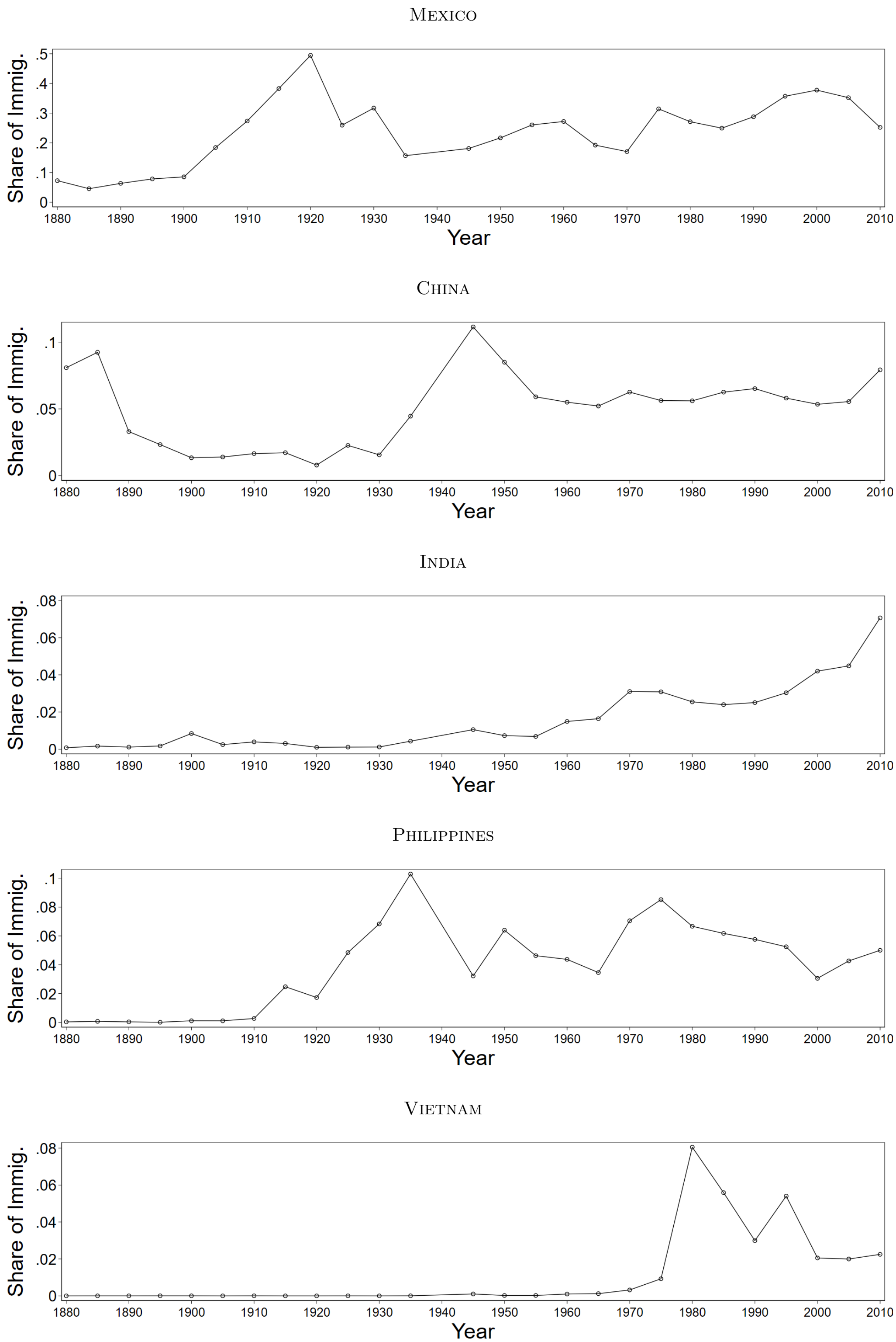
	Δ^{5yr} Job Creation Rate	Δ^{5yr} Job Destruction Rate	Δ^{5yr} Job Growth Rate Skewness
	(1)	(2)	(3)
Immigration$_{d,t}$	0.176***	0.152***	0.019***
	(0.033)	(0.035)	(0.004)
N	6,588	6,588	12,560
First Stage F-Stat	951	951	151
AR Wald F-Test p-value	0.000	0.000	0.000
Geography FE	State	State	State
Time FE	Yes	Yes	Yes

Notes: This table reports the results of our IV specification, described in equation (1), for each of our dependent variables with non-European immigration (1,000s) to d in t as the endogenous variable. Columns 1 and 2 report the results with the job creation rate and job destruction rate as the dependent variable, respectively. Column 3 then provides results for job growth rate skewness as the dependent variable. We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 18: Time Path of Innovation and Wage Elasticities

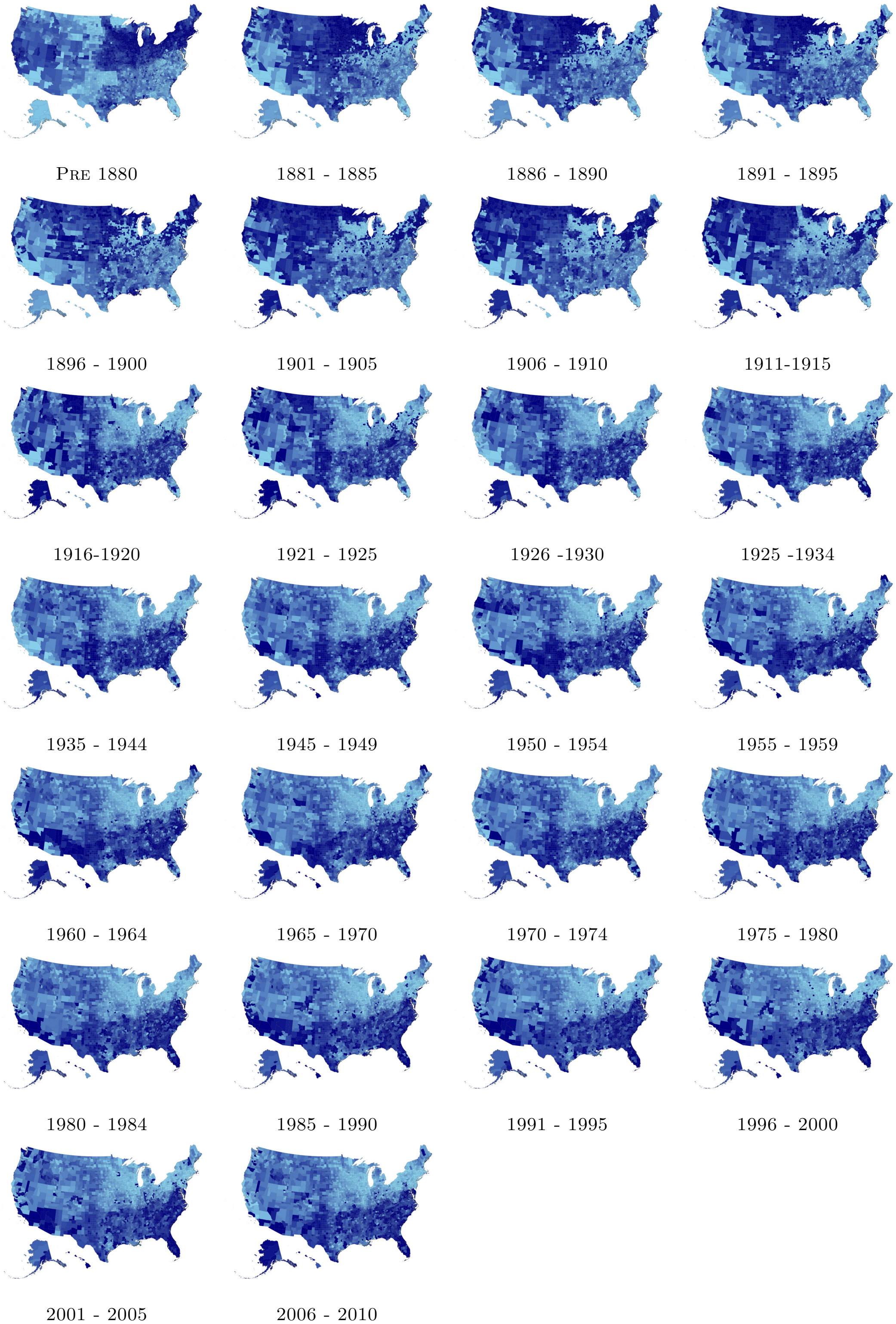
	IHS($Y_{d,t}$)	IHS($Y_{d,t+1}$)	IHS($Y_{d,t+2}$)
	(1)	(2)	(3)
Panel A:		Patent Flows	
IHS($Immigration_{d,t}$)	1.616***	1.712***	1.700***
	(0.156)	(0.274)	(0.351)
N	15,705	15,705	15,705
First Stage F-Stat	109	31	15
AR Wald F-Test p-value	0.000	0.000	0.001
Panel B:		Wages	
IHS($Immigration_{d,t}$)	0.128***	0.151***	0.191*
	(0.016)	(0.050)	(0.099)
N	15,695	15,695	15,695
First Stage F-Stat	152	26	11
AR Wald F-Test p-value	0.000	0.004	0.158
Geography FE	State	State	State
Time FE	Yes	Yes	Yes

Notes: This table displays the results of estimating equation (1), where the dependent variable is the inverse hyperbolic sine (IHS) of patents (Panel A) or IHS of wages (Panel B) and the endogenous variable is the IHS of non-European immigration (1,000s) to d in t. Columns 1 through 3 report regression results where the outcome is measured in period t, $t + 1$, and $t + 2$, respectively; for the regressions in columns 2 and 3 we include controls for the immigration shock in $t + 1$ and the immigration shocks in $t + 1$ and $t + 2$, respectively. We report the first-stage F-statistic on the excluded instrument and the p-value for the Anderson-Rubin Wald F test for each specification. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.



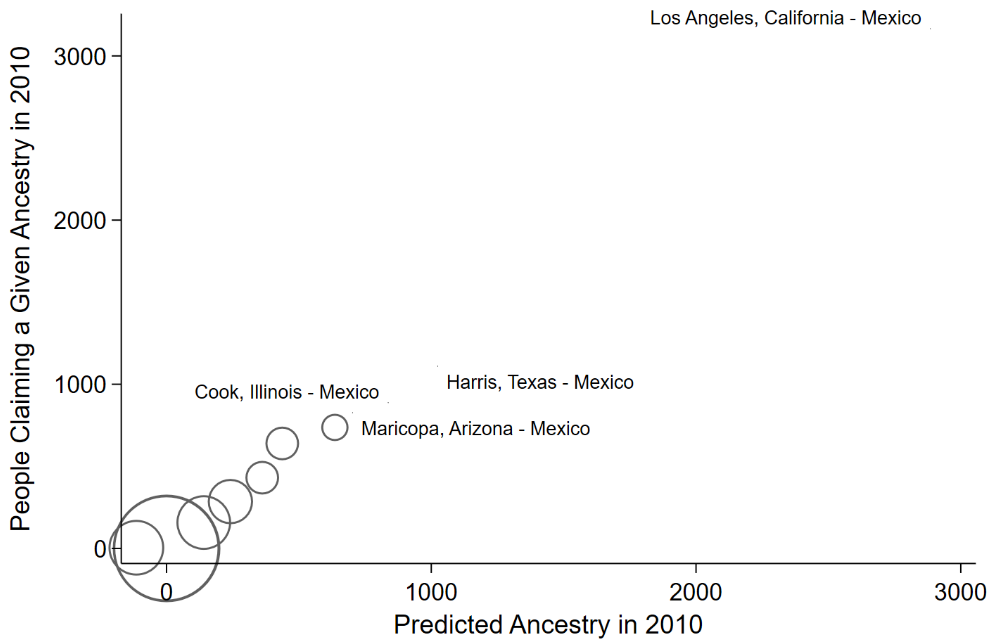
Appendix Figure 1: Share Non-European Immigrants to the US by Origin Country

Notes: This figure plots the share of non-European immigration into the US from the 5 non-European origin nations with the largest cumulative immigration to the US: Mexico, China, India, Philippines, and Vietnam. The figure highlights variation in the push factor, showing how the number of migrants from a given origin country o varies over time.



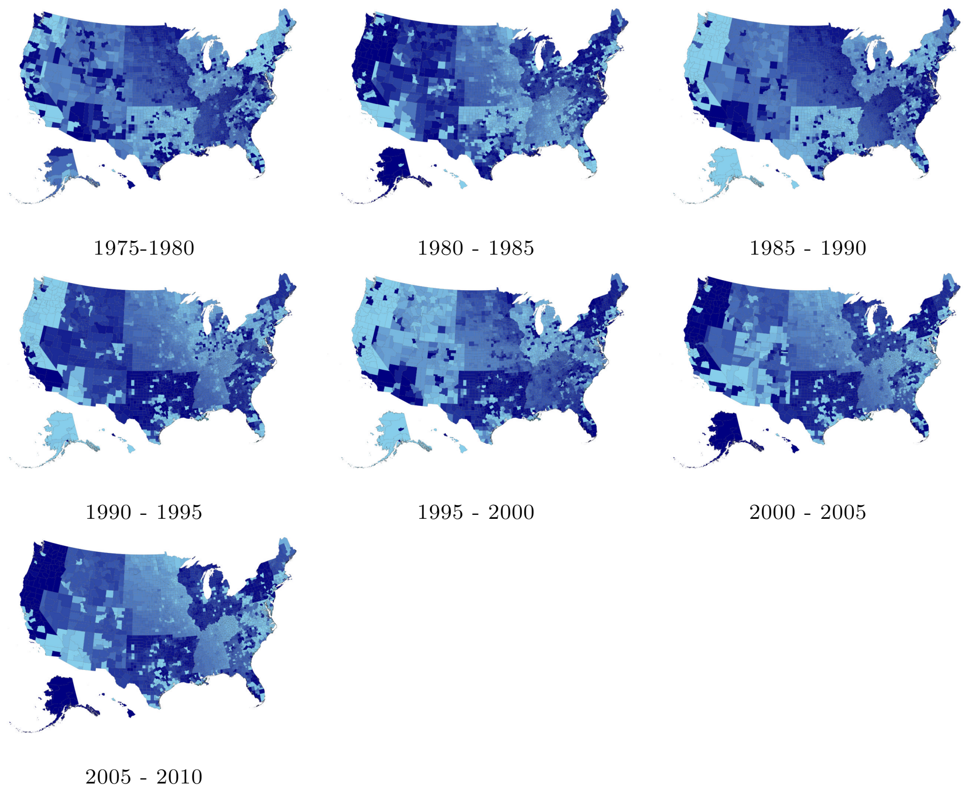
Appendix Figure 2: Destinations of European Immigrants to the US

Notes: This figure maps immigration flows into US counties by 5-year periods (except between 1930 and 1950). We regress the number of European immigrants into US county d at time t, $I_{d,t}$, on destination county d and year t fixed effects, and calculate the residuals. The map's color coding depicts the 20 quantiles of the residuals across counties and within census periods. Darker colors indicate a higher quantile.



Appendix Figure 3: Step 1 – Predicting Ancestry (2010)

Notes: This figure is a binned scatter plot of actual ancestry in 2010 against predicted ancestry, as given in equation (3), where bins are fixed based on predicted ancestry and the size of each circle indicates the log number of observations in a given bin. The labeled counties are those with the highest number of individuals declaring a given ancestry in 2010. The corresponding regression of $A_{o,d,2010}$ on $\hat{A}_{o,d,2010}$, as defined in equation (3), yields an R^2 of 74.9%.



Appendix Figure 4: Immigration Shock Conditional on County and Time Fixed Effects

Notes: This figure maps the instrumented non-European immigration flows into US counties by 5-year periods. We regress the instrument for immigration into US county d at time t on county and year fixed effects, and calculate the residuals. This figure provides a visualization for the immigration shocks used as instruments in the regression shown in column 3 of Table 3. The map's color coding depicts the 200 quantiles of the residuals across counties and within census periods. Darker colors indicate a higher quantile.

B Structural Model and Estimation Appendix

This appendix provides an equilibrium definition and balanced growth path analysis of the quantitative equilibrium regional endogenous growth model. This appendix also provides information on the solution and simulation of the model away from the balanced growth path, together with details of the structural estimation procedure as well as various model extensions.

B.1 Structural Model

B.1.1 Set-up

There are $d = 1, ..., D$ destination regions. There are $o = 1, ..., O$ origin nations. Time t is discrete.

Final Goods Production. A final good is produced by a firm in d with the technology

$$Y_t = Z_{d,t} Q_{d,t} L_{Y,d,t}^{\alpha}$$

where $Q_{d,t}$ is the number of ideas used by the firm in d at time t and $L_{Y,d,t}$ is labor used for production purposes by the firm in region d at time t. The elasticity of output to labor satisfies $0 < \alpha < 1$. The stationary exogenous shock $Z_{d,t}$ to production efficiency satisfies

$$\ln Z_{d,t} = \rho \ln Z_{d,t-1} + \epsilon_{d,t},$$

where the autocorrelation of the shock satisfies $0 < \rho < 1$. We have positive variance with $\epsilon_{d,t} \sim \mathcal{N}(0, \sigma_{\epsilon}^2)$, where $\sigma_{\epsilon} > 0$.

Idea Production. A mass $N_{d,t}$ of new ideas is produced each period by a research firm with an innovation or idea production technology given by

$$N_{d,t} = L_{N,d,t}^{\gamma} \bar{Q}_{d,t-1}^{\zeta},$$

where the elasticity of innovation to researchers satisfies $0 < \gamma < 1$ and the elasticity of innovation to ideas satisfies $0 < \zeta < 1$ where $0 < \gamma + \zeta \leq 1$. There are positive externalities in the growth process, through which past ideas aid in the production of new ideas. $\bar{Q}_{d,t-1}$ is a weighted average of varieties invented across regions at time $t-1$ described further below. Note that we have that the mass of varieties invented in region d evolves according to

$$Q_{d,t} = N_{d,t} + Q_{d,t-1}.$$

In our baseline in the text we assume that $\zeta = 1 - \gamma$, but we quantitatively consider alternative cases allowing for $\gamma + \zeta \neq 1$ below in Figure 7.

Regional Idea Aggregates & Spillovers. The mass of ideas useful to researchers in region d at time is given by

$$\bar{Q}_{d,t} = \prod_{f=1}^{D} Q_{ft}^{\alpha(d,f)}.$$

The elasticity of region d's research-effective ideas to region f's invented ideas, is $\alpha(d,f)$. The elasticities sum to 1 for each region d, i.e.,

$$\sum_f \alpha(d,f) = 1,$$

and the elasticities are proportional to a term declining in the physical distance $\tilde{d}(d,f)$ between d and f with

$$\alpha(d,f) \propto 1 - \delta\tilde{d}(d,f)$$

for some value $\delta \geq 0$. Note that two extreme cases are nested: no idea spillovers ($\delta = \infty$) and full idea spillovers ($\delta = 0$). The baseline model described in the text imposes no spillovers with $\delta = \infty$, in which case $\bar{Q}_{d,t} = Q_{d,t}$. We quantitatively consider a case of full national idea spillovers with $\delta = 0$ below in Figure 5.

Population Structure: Residents, Immigrants, Domestic Migrants, and Ancestry. The population of region d is made up of current residents, domestic migrants, and immigrants, all of whom are members of the labor force. Growth in the population comes only from immigrants and domestic migrants, with accumulation of the labor force over time according to

$$L_{d,t+1} = \sum_{o=1}^{O} I_{o,d,t} + \sum_{d'=1}^{D} M_{d',d,t} + (1-\mu)L_{d,t}.$$

Above, $I_{o,d,t}$ is the mass of immigrants from origin o in destination d at time t. The sum of migrants across all destinations d from a given origin is

$$I_{o,t} = \sum_d I_{o,d,t},$$

and the sum of migrants across all origins o in a given destination is

$$I_{d,t} = \sum_o I_{o,d,t}.$$

Domestic migrants from origin county d' to destination county d at time t are given by $M_{d',d,t}$. Domestic migrants of ancestry o from county d' to county d at time t are indicated by $M_{o,d',d,t}$. A randomly selected fraction $\mu \in (0,1)$ of the domestic population receives a migration opportunity shock, in which case they are able to domestically migrate to any county including, potentially, their own according to the optimization problem laid out below. The total (gross) domestic outmigration from a county d' at time t is given by

$$M_{d',.,t} = \sum_{d=1}^{D} M_{d',d,t},$$

and we must have given the random assignment of the migration shock that $M_{d',.,t} = \mu L_{d',t}$. The total (gross) domestic inmigration to a county d at time t is given by

$$M_{.,d,t} = \sum_{d'=1}^{D} M_{d',d,t}.$$

The stock of residents in destination d with ancestry from origin o in time t is given by $A_{o,d,t}$ which evolves over time according to $A_{o,d,t+1} = I_{o,d,t} + \sum_{d'=1}^{D} M_{o,d',d,t} + (1-\mu)A_{o,d,t}$. Aggregates $A_{o,t}$ and $A_{d,t}$ are defined analogously to $I_{o,t}$ and $I_{d,t}$ above. Given random assignment of the migration shock we have that total (gross) outmigration of ancestry o from county d' at time t is

$$M_{o,d',.,t} = \sum_{d=1}^{D} M_{o,d',d,t},$$

and given random migration shock assignment we also have that $M_{o,d',.,t} = \mu A_{o,d',t}$.

Immigrant Population Dynamics & Destination Choices. The supply of migrants exogenously grows at rate n but is also subject to some stationary iid shocks, i.e.,

$$I_{o,t} = (1+n)^t e^{\nu_{o,t}},$$

where the shocks ν_t^o are normal with mean 0 and variance σ_ν^2. Individual migrants from origin o within the continuum of migrants $I_{o,t}$ statically optimize over destinations d according to a discrete choice framework, taking into account expectations of conditions in all possible destination counties in the following period. A migrant i's expected utility u from migrating to destination d in period t is

$$u_{o,d,t}(i) = e^{-\tau_{o,d,t}} \varepsilon_{d,t}(i) \mathbb{E}_t W_{d,t+1}^{\lambda} \left(\frac{A_{o,d,t+1}}{A_{o,t+1}} \right)^{1-\lambda}$$

where $\varepsilon_{d,t}(i)$ are iid extreme-value distributed shocks across migrants i with dispersion parameter θ, $\tau_{o,d,t} \sim \mathcal{N}(0, \sigma_\tau^2)$ are iid normal shocks representing bilateral costs, and the relative weight on wages versus ancestry composition satisfies $0 < \lambda < 1$. The expectations $\mathbb{E}_t$ in the immigration payoffs are rational and incorporate fully all information available within the model in period t.

Domestic Migrant Dynamics & Destination Choices. Any individual with ancestry o who is a domestic resident of county d' randomly receiving a migration shock statically optimizes their destination county d according to a discrete choice framework, taking into account expectations of conditions in all possible destination counties in the following period. Such a migrant ξ's expected utility $\tilde{u}$ from migrating to destination d in period t is

$$\tilde{u}_{o,d,t}(\xi) = \tilde{\varepsilon}_{d,t}(\xi) \mathbb{E}_t W_{d,t+1}^{\lambda} \left(\frac{A_{o,d,t+1}}{A_{o,t+1}} \right)^{1-\lambda}$$

where $\tilde{\varepsilon}_{d,t}(\xi)$ are iid extreme-value distributed shocks across domestic migrants ξ with dispersion parameter θ, and the relative weight on wages versus ancestry composition satisfies $0 < \lambda < 1$. The expectations $\mathbb{E}_t$ in the domestic migrant's payoffs are rational and incorporate fully all information available within the model in period t.

Resident Labor Supply. Each resident in the continuum of mass $L_{d,t}$ in destination d and time t supplies one unit of labor inelastically to only its local labor market and can choose whether to allocate this labor to the output sector "Y" or the innovation/new ideas sector "N," resulting in the following identity: $L_{Y,d,t} + L_{N,d,t} = L_{d,t}$.

B.1.2 Equilibrium Definition

An equilibrium in this economy is a sequence of local wages $\{W_{d,t}\}_d$, patent prices $\{p_{d,t}\}_d$, immigration flows $\{I_{o,d,t}\}_{o,d}$, $\{I_{d,t}\}_d$, $\{I_{o,t}\}_o$, domestic migration flows $\{M_{o,d',d,t}\}_{o,d',d}$, ancestry levels $\{A_{o,d,t}\}_{o,d}$, $\{A_{d,t}\}_d$, $\{A_{o,t}\}_o$, labor force levels $\{L_{d,t}\}_d$, labor force allocations $\{L_{N,d,t}, L_{Y,d,t}\}_d$, output levels $\{Y_{d,t}\}_d$, patent flows $\{N_{d,t}\}_d$, local idea levels $\{Q_{d,t}\}_d$, research knowledge levels $\{\bar{Q}_{d,t}\}$, and productivity levels $\{Z_{d,t}\}_d$ such that the following conditions hold.

Final Goods Producers Optimize. Taken as given the numeraire price of the nationally traded output good, local wages $W_{d,t}$, patent prices $p_{d,t}$, local idea levels $Q_{d,t-1}$, and local productivity levels $Z_{d,t}$ as given, the competitive local final goods producer in region d chooses patent demand $N_{d,t}$ and production labor demand $L_{Y,d,t}$ to maximize static profits

$$\max_{N_{d,t},L_{Y,d,t}} Z_{d,t}(N_{d,t} + Q_{d,t-1})L^{\alpha}_{Y,d,t} - W_{d,t}L_{Y,d,t} - p_{d,t}N_{d,t}.$$

This optimization leads to two input optimality conditions listed below.

Research Firms Optimize. Taking as given the price of new varieties or patents $p_{d,t}$ and the wage $W_{d,t}$, the research firm demands research labor $L_{N,d,t}$ to maximize flow profits according to

$$\max_{L_{N,d,t}} p_{d,t}L^{\gamma}_{N,d,t}\bar{Q}^{\zeta}_{d,t-1} - W_{d,t}L_{N,d,t}.$$

Note that the underlying timing here requires that the research firm only be paid for a single period's use of their new ideas or varieties, which are assumed to become freely available to all local firms after one period. This optimization leads to two input optimality conditions listed below, which we emphasize represent a static research choice given our assumption on the timing of expiration of protection of new ideas.

Immigrants Optimize. Taking as given wages $\{W_{d,t}\}_d$ in all regions, as well as ancestry levels $\{A_{o,d,t}\}_{o,d}$ and $\{A_{o,t}\}_o$, an individual immigrant i from origin o in period t optimally chooses their destination d to maximize their static expected utility

$$u_{o,d,t}(i) = e^{-\tau_{o,d,t}}\varepsilon_{d,t}(i)\mathbb{E}_t W^{\lambda}_{d,t+1}\left(\frac{A_{o,d,t+1}}{A_{o,t+1}}\right)^{1-\lambda}.$$

As usual, this structure together with the distributional assumption on $\varepsilon_{d,t}(i)$ leads via a discrete-choice law of large numbers across migrants to immigration shares given by

$$I_{o,d,t} = I_{o,t}\left(\frac{e^{-\theta\tau_{o,d,t}}\left(\mathbb{E}_t W^{\lambda}_{d,t+1}\left(\frac{A_{o,d,t+1}}{A_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}{\sum_{k=1}^{D} e^{-\theta\tau_{o,k,t}}\left(\mathbb{E}_t W^{\lambda}_{k,t+1}\left(\frac{A_{o,k,t+1}}{A_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}\right).$$

Domestic Migrants Optimize. Taking as given wages $\{W_{d,t}\}_d$ in all regions, as well as ancestry levels $\{A_{o,d,t}\}_{o,d}$ and $\{A_{o,t}\}_o$, an individual ξ of ancestry o from resident in county d' in period t and hit by the random migration opportunity shock optimally chooses their destination d to maximize their static expected utility

$$\tilde{u}_{o,d,t}(\xi) = \tilde{\varepsilon}_{d,t}(\xi)\mathbb{E}_t W_{d,t+1}^{\lambda}\left(\frac{A_{o,d,t+1}}{A_{o,t+1}}\right)^{1-\lambda}.$$

As usual, this structure together with the distributional assumption on $\tilde{\varepsilon}_{d,t}(\xi)$ leads via a discrete-choice law of large numbers across domestic migrants to shares given by

$$M_{o,d',d,t} = \mu A_{o,d',t}\left(\frac{\left(\mathbb{E}_t W_{d,t+1}^{\lambda}\left(\frac{A_{o,d,t+1}}{A_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}{\sum_{k=1}^{D}\left(\mathbb{E}_t W_{k,t+1}^{\lambda}\left(\frac{A_{o,k,t+1}}{A_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}\right).$$

Note that the share of domestic migrants of ancestry o from county d' to county d is a function of only the ancestry o and destination county d, allowing us to define domestic share variables

$$s_{o,d,t} = \left(\frac{\left(\mathbb{E}_t W_{d,t+1}^{\lambda}\left(\frac{A_{o,d,t+1}}{A_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}{\sum_{k=1}^{D}\left(\mathbb{E}_t W_{k,t+1}^{\lambda}\left(\frac{A_{o,k,t+1}}{A_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}\right)$$

where $M_{o,d',d,t} = \mu A_{o,d',t} s_{o,d,t}$.

Residents Optimize. Individual residents from the labor force of mass $L_{d,t}$ optimally choose whether to supply labor in the ideas sector or output sector in their local region. This optimization requires, if labor used in both sectors is positive in equilibrium, that the workers be indifferent across sectors and face a common wage $W_{d,t}$ in both final goods and idea production.

Note that the assumptions we have made, which constrain all profit maximization problems by firms and labor decisions by immigrants and residents to be static, do not require us to specify further the nature of household preferences, the details of the nationally traded goods market, nor the intertemporal prices of any assets or savings. To characterize the joint equilibrium dynamics of innovation, immigration, wages, and output, these supplemental details can remain unrestricted.

Labor Markets Clear. The total labor demanded in final goods and ideas production in region d equals the labor force $L_{Y,d,t} + L_{N,d,t} = L_{d,t}$, and the labor force evolves dynamically according to the optimal location decisions of immigrants and domestic inmigrants $L_{d,t+1} = I_{d,t} + (1-\mu)L_{d,t} + M_{\cdot,d,t}$.

Ideas Markets Clear. The patent or variety flows demanded by the final goods firm in region d equal the patent or varieties produced by the research firms in region d at the value $N_{d,t}$.

Productivity Levels Evolve Exogenously. Productivity $Z_{d,t}$ in region d evolves stochastically and exogenously according to

$$\ln Z_{d,t} = \rho \ln Z_{d,t-1} + \epsilon_{d,t}$$

where shocks are iid according to $\epsilon_{d,t} \sim \mathcal{N}(0, \sigma_d^2)$.

B.1.3 Equilibrium Solution

The equilibrium of the economy can be summarized as a system of $2O + D \times (3O + 10)$ nonlinear equations in $2O + D \times (3O + 10)$ endogenous and exogenous variables. These equations are listed below.

- O equations characterizing the immigration push process $I_{o,t}$ from origin o to all destinations at time t
$$I_{o,t} = (1+n)^t e^{\nu_{o,t}}, \quad \nu_{ot} \sim N(0, \sigma_\nu^2)$$

- $O \times D$ equations characterizing $I_{o,d,t}$, the immigration flows from origin o to destination d at time t
$$I_{o,d,t} = I_{o,t} \left(\frac{e^{-\theta \tau_{o,d,t}} \left(\mathbb{E}_t W_{d,t+1}^{\lambda} \left(\frac{A_{o,d,t+1}}{A_{o,t+1}} \right)^{(1-\lambda)} \right)^{\theta}}{\sum_{k=1}^{D} e^{-\theta \tau_{o,k,t}} \left(\mathbb{E}_t W_{k,t+1}^{\lambda} \left(\frac{A_{o,k,t+1}}{A_{o,t+1}} \right)^{(1-\lambda)} \right)^{\theta}} \right).$$
$$\tau_{okt} \sim N(0, \sigma_\tau^2)$$
Note that $I_{o,t} = \sum_{d=1}^{D} I_{o,d,t}$ is redundant based on the equations above.

- OD equations characterizing $s_{o,d,t}$, the domestic migration shares of flows of ancestry o potential migrants to destination d at time t
$$s_{o,d,t} = \left(\frac{\left(\mathbb{E}_t W_{d,t+1}^{\lambda} \left(\frac{A_{o,d,t+1}}{A_{o,t+1}} \right)^{(1-\lambda)} \right)^{\theta}}{\sum_{k=1}^{D} \left(\mathbb{E}_t W_{k,t+1}^{\lambda} \left(\frac{A_{o,k,t+1}}{A_{o,t+1}} \right)^{(1-\lambda)} \right)^{\theta}} \right).$$
Note that $M_{o,d',d,t} = \mu A_{o,d',t} s_{o,d,t}$ are redundant given $s_{o,d,t}$ and $A_{o,d',t}$.

- $O \times D$ equations linking ancestry shares to immigration and domestic migration flows
$$A_{o,d,t+1} = (1-\mu) A_{o,d,t} + I_{o,d,t} + \sum_{d'=1}^{D} \mu A_{o,d',t} s_{o,d,t}$$

- O equations linking total ancestry stocks to regional ancestry stocks
$$A_{o,t} = \sum_{d=1}^{D} A_{o,d,t}$$

- D equations linking population dynamics to immigration and domestic migration flows
$$L_{d,t+1} = (1-\mu) L_{d,t} + \sum_{o=1}^{O} I_{o,d,t} + \sum_{o=1}^{O} \sum_{d'=1}^{D} \mu A_{o,d',t} s_{o,d,t}$$

- D equations with the final goods production function for $Y_{d,t}$

$$Y_{d,t} = Z_{d,t} Q_{d,t} L_{Y,d,t}^{\alpha}$$

- D equations characterizing exogenous local productivity dynamics

$$\ln Z_{d,t} = \rho \ln Z_{d,t-1} + \epsilon_{d,t}, \quad \epsilon_{d,t} \sim \mathcal{N}(0, \sigma_d^2).$$

- D equations with the idea production function for the mass of new ideas $N_{d,t}$

$$N_{d,t} = L_{N,d,t}^{\gamma} \bar{Q}_{d,t-1}^{\zeta}$$

- D equations characterizing idea dynamics in each region

$$Q_{d,t} = N_{d,t} + Q_{d,t-1}.$$

- D equations summarizing spillovers through the effective ideas available to researchers in d at time t, $\bar{Q}_{d,t}$:

$$\bar{Q}_{d,t} = \prod_{f=1}^{D} Q_{ft}^{\alpha(d,f)}.$$

- D equations linking labor used in production $L_{Y,d,t}$ inversely to the wage

$$\alpha Z_{d,t} Q_{d,t} L_{Y,d,t}^{\alpha-1} = W_{d,t}$$

- D equations linking labor used in research $L_{N,d,t}$ inversely to the wage

$$\gamma p_{d,t} L_{N,d,t}^{\gamma-1} \bar{Q}_{d,t-1}^{\zeta} = W_{d,t}.$$

- D equations linking the price of new ideas positively to the local productivity shock and labor used in production.

$$Z_{d,t} L_{Y,d,t}^{\alpha} = p_{d,t}.$$

- D equations for labor market clearing

$$L_{N,d,t} + L_{Y,d,t} = L_{d,t}$$

Balanced Growth Path Growth Rates. We say that variable X grows at rate g_X if $X_t = (1 + g_X) X_{t-1}$ or equivalently if $X_t \propto (1 + g_X)^t$. We guess and verify that the equilibrium conditions are satisfied with a steady state growth path structure. Assume that all shocks are equal to 0, i.e., $\tau_{o,d,t} = 0$, $\epsilon_{d,t} = 0$, and $\nu_{o,t} = 0$. Note that if g_Q is the growth rate of $Q_{d,t}$ for each region, then $\bar{Q}_{d,t}$ also trivially grows at rate g_Q, since $\sum_f \alpha(d,f) = 1$ for all d. Then, note that the growth rate of new ideas in each region is given by

$$\frac{N_{d,t}}{Q_{d,t-1}} = \frac{L_{N,d,t}^{\gamma} \bar{Q}_{d,t-1}^{\zeta}}{Q_{d,t-1}}$$

$$= \left(\frac{L_{N,d,t}^{\gamma}}{Q_{d,t-1}^{1-\zeta}} \right) \left(\frac{\bar{Q}_{d,t-1}}{Q_{d,t-1}} \right)^{\zeta}$$

On a balanced growth path we have

$$g_Q = \frac{N_{d,t}}{Q_{d,t-1}}$$

$$g_Q = \left(\frac{L_{N,d,t}^{\gamma}}{Q_{d,t-1}^{1-\zeta}} \right) \left(\frac{\bar{Q}_{d,t-1}}{Q_{d,t-1}} \right)^{\zeta}$$

$$g_Q \propto \frac{L_{N,d,t}^{\gamma}}{Q_{d,t-1}^{1-\zeta}}$$

which implies that

$$L_{N,d,t}^{\gamma} \propto Q_{d,t-1}^{1-\zeta} \propto Q_{d,t}^{1-\zeta}.$$

$$Q_{d,t} \propto L_{N,d,t}^{\frac{\gamma}{1-\zeta}}.$$

So we conclude that

$$1 + g_N = 1 + g_{\bar{Q}} = 1 + g_Q = (1 + g_{L_N})^{\frac{\gamma}{1-\zeta}}.$$

Intuitively, this means that in the long run, only increased research labor input drives growth, a direct implication of the fact that this model falls into the class of semi-endogenous growth models from Jones (1995). Recall that the optimality condition for ideas in goods production is

$$p_{d,t} = Z_{d,t} L_{Y,d,t}^{\alpha},$$

so on a steady state growth path we have

$$1 + g_P = (1 + g_{L_Y})^{\alpha}.$$

The optimality condition for labor demand in innovation is

$$W_{d,t} = \gamma p_{d,t} L_{N,d,t}^{\gamma-1} \bar{Q}_{d,t-1}^{\zeta}.$$

But we have that $L_{N,d,t}^{\gamma} \propto \bar{Q}_{d,t-1}^{1-\zeta}$ on a steady state growth path (from the patenting equation arguments above) so that

$$W_{d,t} \propto p_{d,t} \frac{\bar{Q}_{d,t-1}^{1-\zeta} \bar{Q}_{d,t-1}^{\zeta}}{L_{N,d,t}} = p_{d,t} \frac{\bar{Q}_{d,t-1}}{L_{N,d,t}}$$

so that

$$1 + g_W = (1 + g_P) \frac{(1 + g_{\bar{Q}})}{(1 + g_{L_N})} = (1 + g_{L_Y})^{\alpha} \frac{(1 + g_{L_N})^{\frac{\gamma}{1-\zeta}}}{(1 + g_{L_N})} = (1 + g_{L_Y})^{\alpha} (1 + g_{L_N})^{\frac{\gamma}{1-\zeta} - 1}.$$

But then from the optimality condition for labor demand in production we also have that

$$W_{d,t} = \alpha Z_{d,t} Q_{d,t} L_{Y,d,t}^{\alpha-1},$$

so that on a steady-state growth path

$$1 + g_W = (1 + g_Q)(1 + g_{L_Y})^{\alpha-1}$$
$$1 + g_W = (1 + g_{L_N})^{\frac{\gamma}{1-\zeta}}(1 + g_{L_Y})^{\alpha-1}.$$

Equalizing the expressions for $1 + g_W$ from the production and innovation labor demand optimality conditions yields

$$(1 + g_{L_N})^{\frac{\gamma}{1-\zeta}}(1 + g_{L_Y})^{\alpha-1} = (1 + g_{L_Y})^{\alpha}(1 + g_{L_N})^{\frac{\gamma}{1-\zeta}-1},$$
$$1 + g_{L_N} = 1 + g_{L_Y}.$$

But then since $L_{d,t} = L_{Y,d,t} + L_{N,d,t}$, we also have $1 + g_L = 1 + g_{L_Y} = 1 + g_{L_N}$. Now, also note that since

$$I_{o,t} = (1 + n)^t e^{\nu_{o,t}},$$

we immediately see that on a growth path $1 + g_{I_o} = 1 + n$. Since the endogenous immigration flows $I_{o,d,t}$ are proportional to $I_{o,t}$ on a growth path, we also have $1 + g_{I_o} = 1 + g_{I_{o,d}}$. Since the ancestry accumulation equations imply (once the stationarity of the domestic migration shares $s_{o,d,t}$ on a steady state growth path is noted) that ancestry is proportional to immigration flows, we also have that $1 + g_{A_{o,d}} = 1 + g_{A_o} = 1 + n$. And therefore, since the labor accumulation equations also imply proportionality between total labor and immigration and ancestry, we have $1 + g_L = 1 + n$. In other words, all labor or population outcomes (total and disaggregated immigration, total and disaggregated domestic migration, total and disaggregated ancestry, total and disaggregated labor forces) all grow at rate $1 + n$ on a steady state growth path, driven by the growth in immigration flows at rate $1 + n$. But then at this point we can write several growth rates from above more explicitly, i.e.,

$$1 + g_Q = 1 + g_{\bar{Q}} = 1 + g_N = (1 + n)^{\frac{\gamma}{1-\zeta}}$$
$$1 + g_p = (1 + n)^{\alpha}$$
$$1 + g_W = (1 + n)^{\frac{\gamma}{1-\zeta}+\alpha-1}.$$

Now from the goods production function we also have

$$Y_{d,t} = Z_{d,t} Q_{d,t} L^{\alpha}_{Y,d,t}$$

implying

$$1 + g_Y = (1 + g_Q)(1 + g_{L_Y})^{\alpha} = (1 + n)^{\frac{\gamma}{1-\zeta}}(1 + n)^{\alpha} = (1 + n)^{\frac{\gamma}{1-\zeta}+\alpha}.$$

Therefore we immediately have that the growth rate of per capita output is

$$1 + g_{Y/L} = (1 + g_Y)/(1 + n) = (1 + n)^{\frac{\gamma}{1-\zeta}+\alpha-1} = 1 + g_W,$$

i.e., wages and per capita output grow at the same rate. Note that for wages and per-capita output to grow at a positive rate we must have the following parametric restriction

$$\frac{\gamma}{1 - \zeta} + \alpha - 1 > 0.$$

In the constant returns innovation function case, our baseline model with $\gamma = 1 - \zeta$, we have that this restriction is always satisfied since $\alpha > 0$.[32] But with weaker long-run externalities from idea stocks if $\zeta < 1 - \gamma$ the condition is needed to ensure that ideas have a large enough influence on the marginal product of labor to overcome the long-run neoclassical impact of growing labor supply.

[32] The condition is also satisfied in our robustness checks to multiples cases with $\zeta \neq 1 - \gamma$ in Figure 7 below.

Balanced Growth Path Equilibrium Conditions. Given the derivations above of BGP growth rates, we can scale or detrend the variables and equations above to express them in stationary form away from the BGP. The number of variables is again $2O + D \times (3O + 10)$, denoted with lowercase labels:

1. $i_{o,t} = \frac{I_{o,t}}{(1+n)^t}$, O immigration supply shocks
2. $i_{o,d,t} = \frac{I_{o,d,t}}{(1+n)^t}$, $O \times D$ immigration flows to region d from o at time t
3. $s_{o,d,t}$, $O \times D$ domestic migration flow shares of ancestry o domestic migrants to destination d at time t are already stationary
4. $a_{o,d,t} = \frac{A_{o,d,t}}{(1+n)^t}$, $O \times D$ ancestry stocks from o in region d in time t
5. $a_{o,t} = \frac{A_{o,t}}{(1+n)^t}$, O ancestry stocks from o in total in time t
6. $l_{d,t} = \frac{L_{d,t}}{(1+n)^t}$, D total labor stocks
7. $l_{N,d,t} = \frac{L_{N,d,t}}{(1+n)^t}$, D labor inputs used in innovation
8. $l_{Y,d,t} = \frac{L_{Y,d,t}}{(1+n)^t}$, D labor inputs used in production
9. $y_{d,t} = \frac{Y_{d,t}}{(1+n)^{\left(\frac{\gamma}{1-\zeta}+\alpha\right)t}}$, D outputs
10. D values of $z_{d,t}$, which is already stationary productivity $z_{d,t} = Z_{d,t}$
11. $n_{d,t} = \frac{N_{d,t}}{(1+n)^t}$, D masses of new ideas
12. $q_{d,t} = \frac{Q_{d,t}}{(1+n)^{\left(\frac{\gamma}{1-\zeta}\right)t}}$, D masses of ideas invented locally
13. $\bar{q}_{d,t} = \frac{\bar{Q}_{d,t}}{(1+n)^{\left(\frac{\gamma}{1-\zeta}\right)t}}$, D aggregates of ideas useful for innovation locally
14. $w_{d,t} = \frac{W_{d,t}}{(1+n)^{\left(\frac{\gamma}{1-\zeta}+\alpha-1\right)t}}$, D wages
15. $p_{d,t} = \frac{p_{d,t}}{(1+n)^{\alpha t}}$, D prices of new ideas

These stationary variables are pinned down by the same number of nonlinear equations in stationary form, which are equivalent to the raw equilibrium conditions above but simply rescaled. The equations are:

1. Immigration push shock distributions

$$i_{o,t} = e^{\nu_{o,t}}$$

2. Endogenous immigration flows

$$i_{o,d,t} = i_{o,t}\left(\frac{e^{-\theta\tau_{o,d,t}}\left(\mathbb{E}_t w_{d,t+1}^{\lambda}\left(\frac{a_{o,d,t+1}}{a_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}{\sum_{k=1}^{D} e^{-\theta\tau_{o,k,t}}\left(\mathbb{E}_t w_{k,t+1}^{\lambda}\left(\frac{a_{o,k,t+1}}{a_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}\right).$$

3. Endogenous domestic migration shares

$$s_{o,d,t} = \left(\frac{\left(\mathbb{E}_t w_{d,t+1}^{\lambda}\left(\frac{a_{o,d,t+1}}{a_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}{\sum_{k=1}^{D}\left(\mathbb{E}_t w_{k,t+1}^{\lambda}\left(\frac{a_{o,k,t+1}}{a_{o,t+1}}\right)^{(1-\lambda)}\right)^{\theta}}\right).$$

4. Ancestry accumulation equations

$$a_{o,d,t+1} = \frac{1}{1+n}\left((1-\mu)a_{o,d,t} + i_{o,d,t} + \sum_{d'=1}^{D} s_{o,d,t}\mu a_{o,d',t}\right)$$

$$a_{o,d,t+1} = \frac{1}{1+n}\left((1-\mu)a_{o,d,t} + i_{o,d,t} + s_{o,d,t}\mu\sum_{d'=1}^{D} a_{o,d',t}\right)$$

$$a_{o,d,t+1} = \frac{1}{1+n}\left((1-\mu)a_{o,d,t} + i_{o,d,t} + s_{o,d,t}\mu a_{o,t}\right)$$

5. Ancestry across regions identity

$$a_{o,t} = \sum_{d=1}^{D} a_{o,d,t}$$

6. Labor force accumulation equations

$$l_{d,t+1} = \frac{1}{1+n}\left((1-\mu)l_{d,t} + \sum_{o=1}^{O} i_{o,d,t} + \sum_{d'=1}^{D}\sum_{o=1}^{O} s_{o,d,t}\mu a_{o,d',t}\right)$$

$$= \frac{1}{1+n}\left((1-\mu)l_{d,t} + \sum_{o=1}^{O} i_{o,d,t} + \sum_{o=1}^{O} s_{o,d,t}\mu\sum_{d'=1}^{D} a_{o,d',t}\right)$$

$$= \frac{1}{1+n}\left((1-\mu)l_{d,t} + \sum_{o=1}^{O} i_{o,d,t} + \sum_{o=1}^{O} s_{o,d,t}\mu a_{o,t}\right)$$

7. Labor market clearing equations

$$l_{d,t} = l_{Y,d,t} + l_{N,d,t}$$

8. Output production functions

$$y_{d,t} = z_{d,t}q_{d,t}l_{Y,d,t}^{\alpha}$$

9. Regional productivity shocks stochastic processes

$$\ln z_{d,t} = \rho \ln z_{d,t-1} + \epsilon_{d,t}$$

10. Idea production functions

$$n_{d,t} = l_{N,d,t}{}^{\gamma} \bar{q}_{d,t-1}^{\zeta} (1+n)^{\frac{\gamma\zeta}{\zeta-1}}$$

11. Idea accumulation equations

$$q_{d,t} = n_{d,t} + \left(\frac{1}{1+n}\right) q_{d,t-1}$$

12. Regional research knowledge aggregators

$$\bar{q}_{d,t} = \prod_{f=1}^{D} q_{ft}^{\alpha(d,f)}$$

13. Labor demand optimality for final goods producers

$$w_{d,t} = \alpha z_{d,t} q_{d,t} l_{Y,d,t}^{\alpha-1}$$

14. Labor demand optimality from research firms

$$w_{d,t} = \gamma p_{d,t} l_{n,d,t}^{\gamma-1} \bar{q}_{d,t-1}^{\zeta} (1+n)^{\frac{\gamma\zeta}{\zeta-1}}$$

15. Idea demand optimality from final goods producers

$$p_{d,t} = z_{d,t} l_{Y,d,t}^{\alpha}$$

B.1.4 Numerical Solution and Simulation

We solve the stationary system of equations from section B.1.3 above using second-order perturbation around the nonstochastic BGP of the economy. This nonlinear solution approach is crucial for accounting for the nonlinear mapping from shocks to immigration supply ν_{ot} to immigration flows at the regional level which is state-dependent, varying with predetermined ancestry levels and current wages.

To simulate the model, we draw immigration supply shocks ν_{ot}, regional productivity shocks $\epsilon_{d,t}$, and bilateral immigration cost shocks $\tau_{o,d,t}$ for a large number of periods $T = 1000$, $O = 10$ origins, and $D = 9$ destination regions. Given a parametrization of the model, the exogenous shock draws together with the nonlinear policy functions obtained in our solution step allow for unconditional simulation of the model. This unconditionally simulated data can be processed to produce a range of moments for structural estimation of the model, which is detailed below. Given that we only compute local and symmetric national responses, and given that model nonlinearities relate primarily to asymmetric histories across locations, we compute impulse repsonses using a linearized version of the model.

We implement all of these numerical model steps, i.e., solution, unconditional simulation, and impulse response calculations, using Dynare within a MATLAB environment. Given the smooth nature of our equilibrium conditions, the well behaved non-stochastic BGP, and the large number of equilibrium conditions, the Dynare package is a natural choice for numerical analysis in this context.

B.2 Structural Estimation

To parameterize our model, we first externally calibrate or fix the magnitudes of various parameters to values commonly employed in the literature. To match our empirical approach, we solve and simulate the model in five-year periods, and we choose the value n of exogenous population growth n, equal to the BGP growth rate of knowledge or ideas in our economy, to be 2% on an annualized basis. Note that the value α has a literal labor share in output interpretation, but α also has an interpretation in many tightly related growth models as the parameter governing markups for intermediate goods firms. So we choose α to imply a round value of a 20% markup, i.e., $\alpha = 1/1.2 \approx 0.8$ in our baseline. Based on the analysis in Caliendo et al. (2019), we match an elasticity of immigration shares to local wages of 0.5 through the choices $\lambda = 0.5$ and $\theta = 1$. We also choose the domestic migration shock probability μ to guarantee a steady-state mobility rate of around 5.6% on an annualized basis from CPS data in the 1980-2010 period (US Census Bureau, 2022).

Estimated Parameters. After external calibration of the parameters noted above, there are seven remaining parameters in our model:

1. Elasticity of local innovation to researchers γ
2. Autocorrelation of regional productivity shocks ρ
3. Volatility of regional productivity shocks σ_ϵ
4. Volatility of immigration supply shocks σ_ν
5. Volatility of bilateral immigration cost shocks σ_τ
6. Linear decline in research knowledge spillovers with distance δ
7. Elasticity of local innovation to idea stocks ζ

We structurally estimate the values of the first five parameters above using an overidentified simulated method of moments (SMM) procedure outlined below.[33] For the sixth parameter, related to idea spillovers, we explore the implications of varying the parameter to extreme values implying full, frictionless spillovers of ideas across regions ($\delta = 0$) versus no idea spillovers across idea-autarkic regions ($\delta = \infty$, our baseline described in the main text). For each of these alternative cases for idea spillovers, we implement the full SMM estimation procedure below conditional upon the appropriate value of δ. Note also that the values we choose for δ, 0 vs ∞, imply spillovers that are either non-existent or independent of distance, implying that we do not need to explicitly specify the geographic structure of the model. Finally, for the seventh parameter ζ, we make the baseline assumption $\zeta = 1 - \gamma$ of constant returns in innovation, relaxing this assumption in robustness checks in Figure 7 below.

[33] Note that one of our target moments is an IV regression coefficient, leading us to sometimes interchangeably refer to this approach as an indirect inference procedure in the main text.

Target Moments. To discipline the values of the five estimated parameters, we target the value of six related moments:

1. IV coefficient estimating the elasticity of patenting to immigration at the county d level
2. Standard deviation of origin-level immigration flows at the origin o level
3. Standard deviation of destination d-level immigration flows
4. Standard deviation of origin $o \times$ destination d-level immigration flows
5. Autocorrelation of output per capita at the county d level
6. Autocorrelation of patenting at the county d level

Moments 1-4 and 6 are directly computable within the 1975-2010 sample used for the main reduced-form empirical results in the paper. We compute the fifth moment based on the BEA (2021)'s county level GDP estimates for five-year periods within the available 2001-19 window.

Although the mapping from parameters to moments in our model is nonlinear and joint in nature, there are certain parameters particularly influential for determining the value of individual moments in our simulation. In particular, the IV-estimated elasticity of patenting to immigration moves directly in the model with the underlying local elasticity of innovation to researchers γ. The volatilities of origin-, destination-, and origin $\times$ destination-level immigration flows depend upon the volatilities of origin-, destination-, and origin $\times$ destination-level exogenous shocks σ_ν, σ_ϵ, and σ_τ, respectively. The autocorrelations of per-capita output and patenting increase with the autocorrelation of underlying regional productivity shocks ρ.

SMM Objective and Standard Errors. First, we collect the five estimated parameters into the vector $\theta = (\gamma, \rho, \sigma_\epsilon, \sigma_\nu, \sigma_\tau)'$. We similarly collect the values of the six target moments m into vectors, denoting by $m(X)$ the value of these moments in the empirical data X, denoting by $m^S(\theta)$ the values of these moments based on our unconditionally simulated data in the model, and denoting by $m(\theta)$ the population values of these moments. Our SMM estimation procedure generates point estimates $\hat{\theta}$ as the solution to the minimization problem

$$\min_\theta (m(X) - m^S(\theta))' W (m(X) - m^S(\theta)),$$

where W is a symmetric weighting matrix for the simulated moment deviations. If the moment vector behaves in an asymptotically normal fashion according to

$$\sqrt{N}\,(m(X) - m(\theta)) \to_d \mathcal{N}(0, V),$$

then standard SMM derivations yield asymptotic normality for the parameter estimates

$$\sqrt{N}\left(\hat{\theta} - \theta\right) \to_d \mathcal{N}(0, \Sigma),$$

where the asymptotic variance Σ is given by the sandwich formula

$$\Sigma = \left(1 + \frac{1}{S}\right)\left(\frac{\partial m'}{\partial \theta} W \frac{\partial m}{\partial \theta}\right)^{-1} \frac{\partial m'}{\partial \theta} W V W \frac{\partial m}{\partial \theta}\left(\frac{\partial m'}{\partial \theta} W \frac{\partial m}{\partial \theta}\right)^{-1}$$

Above, $\frac{\partial m}{\partial \theta}$ is the Jacobian of model moments to parameters and S is the ratio of the simulated to empirical sample sizes.

Some practical decisions must be made to compute point estimates $\hat{\theta}$ as well as a feasible estimate $\hat{\Sigma}$ of the asymptotic variance above. First, we use the identity weighting matrix $W = I$. We compute the Jacobian numerically using finite differences relative to our point estimates. To compute an estimate of the moment covariance matrix $\hat{V}$, we first impose diagonality across the moments which all differ by aggregation level and sample size. We then compute asymptotic variances for each moment using a combination of standard analytic formulas, clustering by state, and the Delta method. The resulting standard errors reported are given by $\left(\frac{\text{diag}\hat{\Sigma}}{N}\right)^{0.5}$. The main text's Table 6 reports parameter estimates, standard errors, and model vs data moments for our baseline case with no idea spillovers, and Table 19 reports the same information for the alternative case with full idea spillovers.

B.3 Immigration and Naturalization Act Accounting Exercise

In order to model a scenario that mimics a hypothetical failure of the Immigration and Naturalization Act (INA) to pass in 1965, we compute the counterfactual evolution over time of macroeconomic aggregates in a version of our model in which we feed a string of negative exogenous shocks to immigration supply, symmetric across origins, which reduce the US population growth rate by 16% relative to our baseline calibrated model.

To compute this 16% value, we proceed as follows. We first extract overall population counts and counts of the population of the foreign born from decadal US Census tabulations in the 1860-2010 time period (US Census Bureau, 2014). The total population in Census year t, P_t, is made up of native, N_t, and foreign-born individuals, F_t,

$$P_t = N_t + F_t.$$

We can then decompose the growth rate of the US population as a whole into a fraction accounted for by natives ($\Delta N_t/\Delta P_t$) and the remaining fraction accounted for by the foreign born ($\Delta F_t/\Delta P_t$),

$$\frac{\Delta P_t}{P_t} = \frac{\Delta P_t}{P_t}\left(\frac{\Delta N_t}{\Delta P_t} + \frac{\Delta F_t}{\Delta P_t}\right).$$

The share of the US population growth rate accounted for by natives fell from 95% in the decades before the INA (1860-1960) to 80% in the decades after (1970-2010).

We then assume that the *only* exogenous change in a world with the INA compared to a world without is the process for immigration. The growth of the native population, as a share of the US population, remains constant, ${}^{\Delta N_t}/_{P_t}|_{no\,INA} = {}^{\Delta N_t}/_{P_t}|_{INA}$. To match the decrease of the share of the population growth rate coming from natives (${}^{\Delta N_t}/_{\Delta P_t}$) from 95% in the pre-INA period to 80% in the post-INA period, we calibrate a world without the INA by feeding a string of negative exogenous shocks to immigration supply, symmetric across regions, such that the US population growth rate declines by 16%.[34]

[34]The population growth rate is x% lower in a world without versus with the INA, $g|_{no\,INA} = (1-x)g|_{INA}$. Imposing that the contribution of natives to the population remains constant, $g|_{no\,INA}{}^{\Delta N_t}/_{\Delta P_t}|_{no\,INA} = g|_{INA}{}^{\Delta N_t}/_{\Delta P_t}|_{INA}$, and plugging in the empirical contribution of natives to population growth pre- and post-INA (95% and 80% respectively), we get $x = 1 - {}^{0.8}/_{0.95} \approx 0.16$.

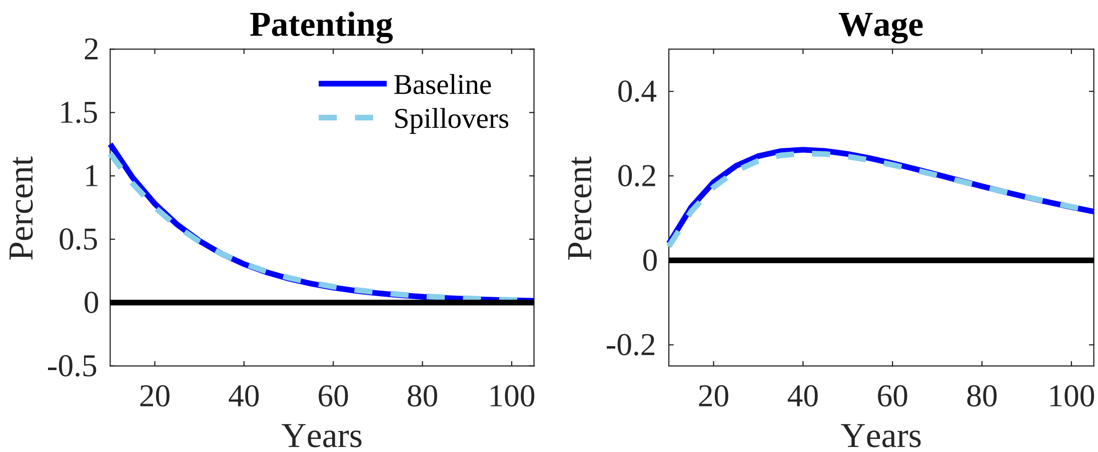
We can compute the total difference in immigration over 45 years (corresponding to 1965-2010) in our two scenarios, with and without the INA. Given that the reduction in the annual population growth rate from 1.03% to 0.87% is solely due to a reduction in immigration, there would have been 21 million fewer migrants.[35]

Appendix Table 19: Parameters and Model Fit, Full Idea Spillovers

Panel A: Moments	Data	Model
IV coeff., patenting$_{d,t}$ on immigration $I_{d,t}$	1.6519	1.6418
	(0.1500)	
Std. deviation, o immigration $I_{o,t}$	0.4061	0.3931
	(0.0284)	
Std. deviation d immigration $I_{d,t}$	0.1794	0.1815
	(0.0110)	
Std. deviation, o-d immigration $I_{o,d,t}$	0.0716	0.1188
	(0.0117)	
Autocorrelation, output per capita $Y_{d,t}/L_{d,t}$	0.9611	0.9518
	(0.0057)	
Autocorrelation, patenting$_{d,t}$	0.9039	0.8745
	(0.0065)	
Panel B: Estimated Parameters	**Symbol**	**Value**
Elasticity, patenting to labor	γ	0.7674
		(0.1392)
Autocorrelation, county TFP	ρ	0.8681
		(0.0366)
Std. deviation, county TFP shocks	σ_ϵ	0.0239
		(0.0130)
Std. deviation, immigration push shocks	σ_ν	0.5864
		(0.0797)
Std. deviation, bilateral immigration shocks	σ_τ	0.5780
		(0.0714)

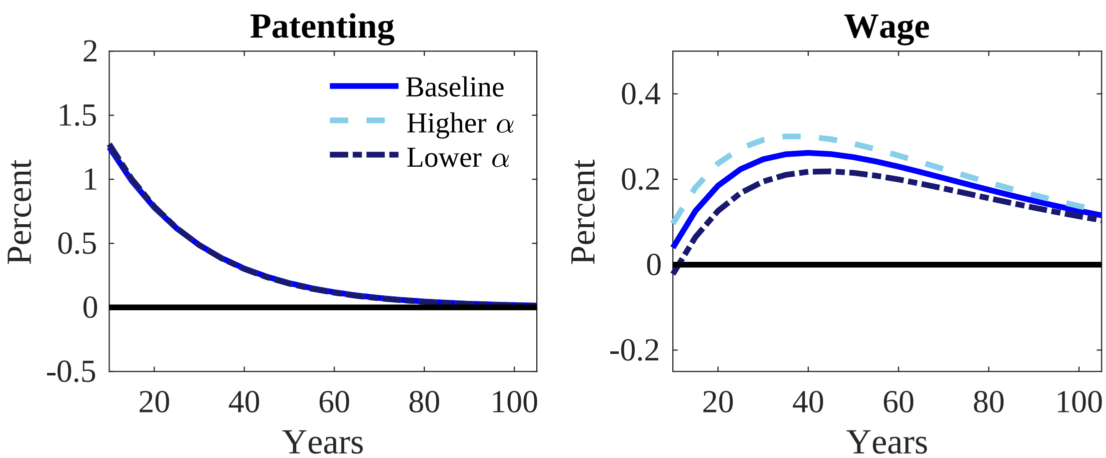
Notes: The table reports the model fit and estimated parameters in the alternative model with full idea spillovers across counties. The top Panel A reports targeted data moments vs simulated model moments. The bottom Panel B reports the estimated parameters. The standard errors, in parentheses beneath moments and estimates, are clustered by state.

[35] The realized US population growth is 1.03% per year, from 195 to 309 million. In a counterfactual scenario without the INA, with an annual population growth rate falling by 16% to 0.87% per year, the total population would grow from 195 to 289 million, 21 million fewer than in the scenario with the INA, entirely attributable to missing migrants.



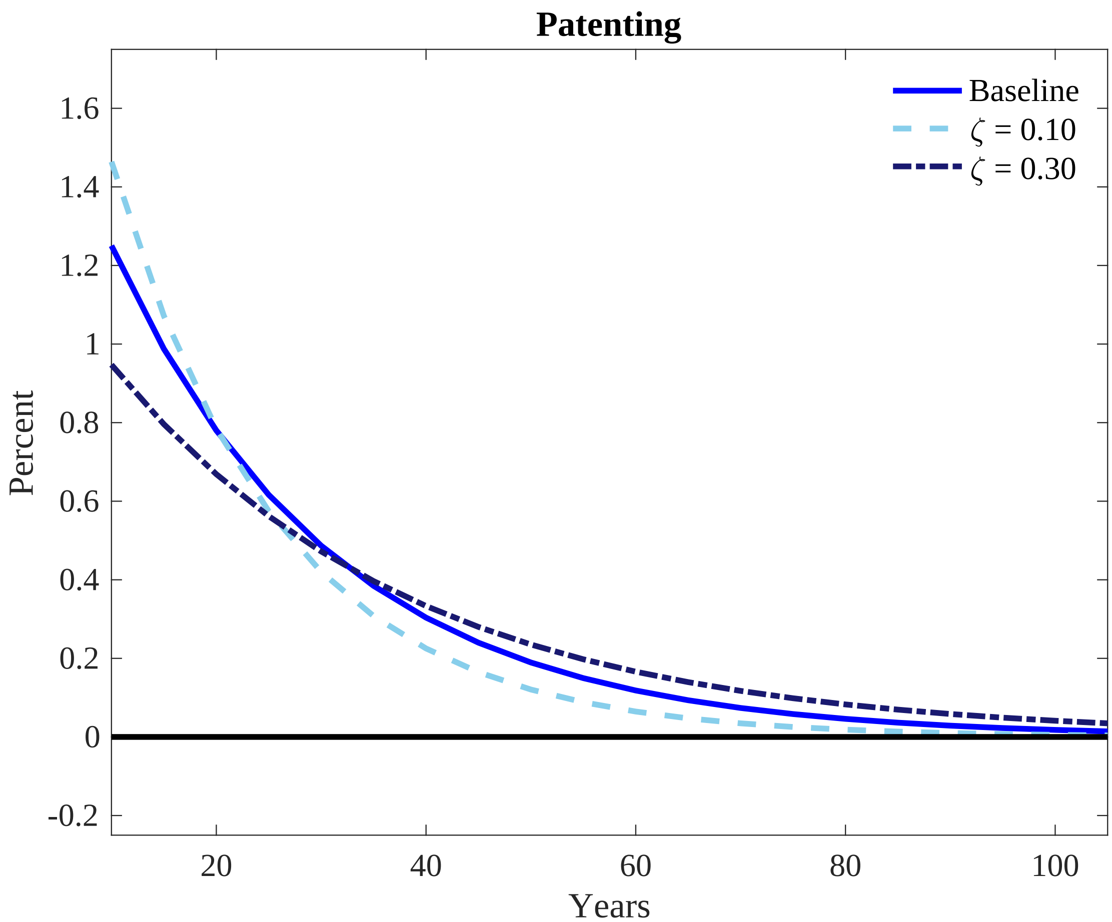
Appendix Figure 5: Full Idea Spillovers in the Model

Notes: The figure plots impulse response functions to a one-standard deviation immigration shock in period 1. The left panel plots patenting $n_{d,t}$. The right panel plots the response of the wage $w_{d,t}$. The immigration shock is from a single origin o, and the responses of the labor force, patenting, and the wage are local responses for a county d. The solid blue line labelled Baseline traces the impact of the immigration shock in our baseline estimated model with no cross-region spillovers. The dashed light blue line labelled Spillovers reports the impact of an immigration shock in our alternative estimated model allowing for full idea spillovers. The responses are in percentage deviations from the balanced growth path.



Appendix Figure 6: Alternative Returns to Scale in the Model

Notes: The figure plots impulse response functions to a one-standard deviation immigration shock in period 1. The left panel plots patenting $n_{d,t}$. The right panel plots the response of the wage $w_{d,t}$. The immigration shock is from a single origin o, and the responses of the labor force, patenting, and the wage are local responses for a county d. The solid blue line labelled Baseline traces the impact of the immigration shock in our baseline estimated model with $\alpha \approx 0.8$. The dashed light blue line labelled Higher α reports the case of $\alpha = 0.95$, while the dashed dot darker blue line labelled Lower α uses $\alpha = 0.7$. The responses are in percentage deviations from the balanced growth path.



Appendix Figure 7: Alternative Returns to Scale in Innovation

Notes: The figure plots impulse response functions of patenting $n_{d,t}$ to a one-standard deviation immigration shock in period 1. The immigration shock is from a single origin o, and the responses of the labor force, patenting, and the wage are local responses for a county d. The solid blue line labelled Baseline traces the impact of the immigration shock in our baseline estimated model with an elasticity of innovation past ideas of $1 - \hat{\gamma} \approx 0.2$. The dashed light blue line instead considers an elasticity of innovation to past ideas of $\zeta = 0.1$ in an extended, re-estimated semiendogenous growth model with innovation function $N_{d,t} = L_{N,d,t}^{\gamma} Q_{d,t-1}^{\zeta}$. The dashed dot darker blue line considers an elasticity of innovation to past ideas of $\zeta = 0.30$ in the extended model, again re-estimated. The responses are in percentage deviations from the balanced growth path.

References

Adão, R., M. Kolesár, and E. Morales (2019): "Shift-share designs: Theory and inference," *The Quarterly Journal of Economics*, 134, 1949–2010.

Angrist, J. D. and J.-S. Pischke (2009): *Mostly harmless econometrics: An empiricist's companion*, Princeton university press.

BEA (2018): "Personal Consumption Expenditures Price Index," data, US Bureau of Economic Analysis.

——— (2021): "GDP by County, Metro, and Other Areas," data, US Bureau of Economic Analysis.

BLS (2018): "Quarterly Census of Employment and Wages," data, US Bureau of Labor Statistics.

Burchardi, K. B., T. Chaney, and T. A. Hassan (2019): "Migrants, Ancestors, and Foreign Investments," *The Review of Economic Studies*, 86, 1448–86.

Caliendo, L., M. Dvorkin, and F. Parro (2019): "Trade and labor market dynamics: General equilibrium analysis of the china trade shock," *Econometrica*, 87, 741–835.

Card, D. (2001): "Immigrant Inflows, Native outflows, and the Local Labor Market Impacts of Higher Immigration," *Journal of Labor Economics*, 19, 22–64.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001): "The NBER Patent Citaitons Data File: Lessons, Insights, and Methodological Tools," NBER Working Paper 8498.

Jones, C. I. (1995): "R&D-Based Models of Economic Growth," *Journal of Political Economy*, 103.

Manson, S., J. Schroeder, D. V. Riper, K. Knowles, T. Kugler, F. Roberts, and S. Ruggles (2023): "IPUMS National Historical Geographic Information System: Version 18.0 [dataset]," data, Integrated Public Use Microdata (IPUMS).

NBER (2018): "US Intercensal Population by County and State 1970-on," data, National Bureau of Economic Research.

Ruggles, S., S. Flood, R. Goeken, J. Grover, E. Meyer, J. Pacas, and M. Sobek (2018-2020): "Integrated Public Use Microdata Series: Version 8.0, 9.0, 10.0 [dataset]," data, University of Minnesota.

US Census Bureau (2013): "Census Regions and Divisions of the United States," data, US Census Bureau.

——— (2014): "The "Second Great Wave" of Immigration: Growth of the Foreign-Born Population Since 1970," Web posting.

——— (2018a): "Business Dynamics Statistics," data, US Census Bureau.

——— (2018b): "Longitudinal Business Database," data, US Census Bureau.

——— (2022): "CPS Historical Migration/Geographic Mobility Tables," data, US Census Bureau.

USPTO (Accessed: Mar. 28-29, 2022): "Data Download Tables," data, U.S. Patent and Trademark Office.