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High-skilled immigration enhances regional entrepreneurship

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Immigrants are highly entrepreneurial. But, what is the broader relationship between high-skilled immigration and regional entrepreneurship activity beyond the ventures that immigrants establish themselves? Using administrative data on newly awarded H-1B visas in the United States, we document a positive relationship between high-skilled immigration and regional entrepreneurship. A doubling of immigrants to a metropolitan statistical area is followed by a 6% increase in entrepreneurship within three years. In contrast, continuing H-1Bs and the arrival of unskilled immigrants (H-2B visas) do not increase regional entrepreneurship. Focusing on Indian immigrants (representing about 70% of all H-1B visas), we find the effect is stronger in metropolitan statistical areas with a larger local Indian population, but not other nationalities, suggesting that presence of conationals facilitates the relationship between high-skilled immigration and regional entrepreneurship. We present this and other evidence as consistent with a knowledge transfer mechanism.

immigration | entrepreneurship | H-1B visas | Startup Cartography Project

Significance

Policy and economic arguments often depend on assumptions of how immigrants shape their destination regions and the extent to which they benefit or compete with natives. This is particularly true for high-skilled immigrants, who bring knowledge but also take some of the highest-paid positions. We present evidence that high-skilled immigrants may promote regional entrepreneurship by increasing the economic potential of other firms in a region. The relationship is stronger in destination regions with a higher presence of conationals. These results suggest an immigration policy promoting high-skilled immigration is beneficial to U.S. regional economic dynamism and growth and presents some determinants driving the size of these effects.

Social science research has revealed numerous economic benefits of high-skilled immigration to host countries (1). One important pathway is through entrepreneurship. Immigrants are overrepresented among startup founders, both for high growth (2) and local firms (3, 4). Research on new immigrant firms (5–9) often departs from the premise that, given the well-documented role of entrepreneurship on local economic growth (10–12), the regional benefits of immigrants on entrepreneurship are substantial.

Yet, this argument presents several inconsistencies and empirical gaps. One, most high-skilled immigrants arrive through employment visas tied to an employer, such as the U.S. H-1B program, that do not allow migrants to be concurrently self-employed. This regulation significantly limits the potential for immigrants under H-1B visas to become full-time entrepreneurs while holding H-1B visas themselves (13). Although it is possible for H-1B workers to be sponsored for the visa by their own startups, it is rare.* Therefore, even if high-skilled immigrants start firms, it usually takes years for entrepreneurship to be legally possible. Two, even if they play a role in shaping entrepreneurship, immigrant firms may displace firms founded by natives, a concern that is common in labor studies (14, 15). Therefore, even though we know immigrants start firms, the effect of high-skilled immigrants on regional entrepreneurship, i.e. beyond the firm level, remains unclear.

Underlying these gaps is not simply the absence of empirical estimates, but more importantly, the scarce attention on the processes through which immigrants could shape regional entrepreneurship. High-skilled immigrants may enhance regional entrepreneurship directly by founding firms or joining startups as early employees (9). In this labor-based mechanism, regional effects are driven by how their employment in startups helps these very firms innovate and grow. Additionally, high-skilled immigrants may also shape regional entrepreneurship indirectly while working in established companies and sharing novel knowledge, ideas, and information with others in the regions where they settle (2, 16–18). The role of high-skilled immigrants transferring knowledge across borders has been well documented for returning nationals (16, 19). Within teams, the effect of immigrants on performance appears to be highly determined by conationals, suggesting that their cultural affinity facilitates mutual knowledge flows (20).

We examine the relationship between high-skilled immigration and regional entrepreneurship. We find that when metropolitan statistical areas (MSAs) receive more high-skilled immigrants, they see subsequent increases in local entrepreneurship, a result that holds when using a shift-share (Bartik) instrumental variables approach to incorporate only the exogenous part of this migration. The effect occurs over time and is present only when new high-skilled immigrants arrive, but not for continuing H-1B visas or unskilled immigrant visas (H-2B). Furthermore, by exploiting differences in

*See *Founders being petitioned by their own startups* for details.

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the density of immigrant population by nationality and the size of the petitioning firm, we find support for a knowledge-transfer based mechanism through regionally embedded social ties (21–23). Specifically, the effect intensifies with the greater presence of other immigrant conationals in the destination regions and is not sensitive to immigration as a whole, consistent with the role of "immigrant enclaves" in facilitating the integration of high-skilled immigrants into a region's entrepreneurial ecosystem (24–27). Together, these results shed light on the indirect effect of H-1B immigrants on regional entrepreneurship through knowledge transfer stemming from relational embeddedness (21–23). In doing so, we document an additional pathway between high-skilled immigrants and entrepreneurship, besides immigrants' well-established role in directly starting firms or contributing as startup employees.

Our study focuses specifically on the U.S. H-1B visa program. The program allows 85,000 new high-skilled foreign nationals (plus some cap-exempt exceptions) to work within specialized roles with U.S.-based employers for up to six years. Studying the effects of the H-1B program at the regional level has been difficult due to two data limitations. First, there is a lack of access to systematic panel data by year and location of H-1B visa recipients, making it difficult to assess the destination region of each visa. And second, while the effect of the visa program on regional entrepreneurship is not simply a change in the quantity of firms but also potentially their quality (growth potential), previous datasets have not incorporated measures of startup quality.

We address these challenges by leveraging newly released data from the U.S. Citizenship and Immigration Services (USCIS) on the approved H-1B visas and their petitioner characteristics, data from the U.S. Department of Labor (DOL) on the labor condition authorizations (LCA)—an antecedent file by firms for requesting a visa—and regional measures of the quantity and quality of entrepreneurship from the Startup Cartography Project (SCP) (28).[†] Using these data, we present complementary analyses that, together, show an important role of skilled immigration on regional entrepreneurship. First, we use a shift-share instrument (31, 32) that takes advantage of the industry of the employer associated with each visa to estimate the number of expected H-1Bs into a region based on the changes that the industry goes through in other regions. This allows us to estimate a two-stage least squares model with the predicted number of visas serving as an instrument for the actual visas arriving into an MSA. This approach addresses a core endogeneity concern that local changes in the receiving region can be correlated with both immigration and entrepreneurship. Second, we use panel data permitting us to include lagged independent variables in our models to study changes in migration conditional on pretrends for each location. Lagging the number of H-1Bs allows us to compare whether H-1Bs predict either future or past entrepreneurship, and hence assess pretrends in the data. Third, we perform comparative placebo tests against migrants on continuing H-1B visas and H-2B visas. Finally, we perform several robustness checks to rule out alternative explanations.

We report four key results. Before elaborating, it is important to emphasize that we recognize both causal and selection-based processes likely contribute to the relationship. Our analyses provide evidence consistent with a positive relationship between H-1B immigration and regional entrepreneurship, but we do not seek to eliminate the important role of immigrants selecting into appropriate regions and the benefits they provide. That is, our results do not disprove the role of selection, but rather 1) establish a robust relationship between high-skilled immigration and regional entrepreneurship, and 2) present evidence that makes a causal interpretation plausible.

[†]We measure quality through the measures developed by Guzman and Stern (29), who use business registration records and the founding characteristics of firms to create predicted estimates of the probability of high growth at founding creating, in essence, a surrogate index for expected future success (30) (*Data*).

Results

1. MSAs That Receive More High-Skilled Immigrants Subsequently Increase Their Regional Entrepreneurship.

High-skilled immigration and MSA entrepreneurship: Preliminary model. We begin by reporting a preliminary model that shows the basic correlation between high-skilled immigration and regional entrepreneurship. Table 1 reports a set of linear regression models on the relationship between high-skilled immigration to an MSA and follow-on entrepreneurship in the MSA. The dependent variable, Regional Entrepreneurship Cohort Potential Index (RECPI), is a measure of the quality-adjusted quantity of new firms, while Startup Formation Rate (SFR) is the count of new firms without incorporating quality (see *Startup Cartography Project* for details). In Model 1, the reported coefficient represents the unconditional correlation between the log of new H-1Bs to an MSA and quality-adjusted quantity of MSA-level entrepreneurship. The coefficient of Log(New H-1Bs) is 0.628 and statistically significant at the $P < 0.01$ level. This coefficient implies that, unconditionally, a region with 20% more newly arrived skilled immigrants has 13% higher quality-adjusted entrepreneurship. Increasing H-1B immigration by 20% is realistic in our data. It translates to an increase of about 55 new H-1Bs immigrants for the average MSA, which receives 275 H-1B visa holders in a given year, on average.

Model 2 adds control variables for population, foreign-born population, and a lagged measure of RECPI two years before. Including this lagged variable accounts for related time-invariant

Table 1. Ordinary Least Squares (OLS) regression models of regional entrepreneurship on high-skilled migration at the MSA level

	Dependent variable:			
	Log(RECPI[t = 0, 1, 2])		Log(SFR[t = 0, 1, 2])	
	(1)	(2)	(3)	(4)
Log(New H-1Bs)	0.628***	0.041***	0.521***	0.022***
	(0.028)	(0.010)	(0.023)	(0.008)
Log(RECPI 2 y ago)		0.788***		
		(0.038)		
Log(SFR 2 y ago)				0.708***
				(0.063)
Foreign born population percentage		0.138		0.085
		(0.234)		(0.199)
Log(Population)		0.189***		0.294***
		(0.039)		(0.062)
State F.E.	No	Yes	No	Yes
Year F.E.	No	Yes	No	Yes
Observations	1,552	1,552	1,552	1,552
R^2	0.612	0.977	0.615	0.976

This table reports the estimates for the effect of the number of new H-1Bs (approved initial H-1Bs) in an MSA at year t = 0 on the MSA's cumulative 3-y RECPI (columns 1 and 2) and 3-y SFR (columns 3 and 4). The dependent variables, cumulative 3-y RECPI and SFR refer to the sum of RECPI and SFR respectively at t = 0, 1, and 2. The specifications in columns 2 and 4 have controls for other MSA characteristics which may impact regional entrepreneurship and startup formation rate. These include RECPI and SFR at $t = -2$, percent of the population that is foreign born at t = 0, and size of the population at t = 0. We report SEs clustered by MSA. Significance denoted as $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

characteristics at the MSA level. Importantly, we also include fixed effects for each state and year. Model 2, therefore, compares how entrepreneurship in MSAs in the same state changes when the number of skilled immigrants changes, controlling for fixed state-level characteristics and national market cycles. The magnitude of the coefficient for Log(New H-1Bs) decreases substantially, but the estimate remains statistically significant at the $P < 0.01$ level. After including controls, increasing skilled immigration by 20% increases entrepreneurship by 0.8% at the regional level.

Models 3 and 4 repeat the same analysis using the number of new firms as the dependent variable without adjusting for their estimated quality. The correlation in Model 4 is about half of that of Model 2, suggesting that skilled immigration not only promotes the entry of new firms in a given region, but also an increase in higher quality new ventures.

One potential interpretation of these results is that H-1B workers sort into MSAs with certain characteristics such as high levels of innovation and availability of local financial capital. *SI Appendix*, Table S2 indeed supports this. This presents the possibility that there are regional features that might increase the number of newly arrived skilled immigrants while simultaneously benefiting regional entrepreneurship. In all likelihood, both selection processes and the treatment effect of skilled immigration contribute to regional entrepreneurship. In the following sections, we attempt to isolate the exogenous variation in the arrival of H-1B workers to present evidence consistent with the presence of a treatment effect.

Shift-share instrumental variables estimate. A concern with the results above is omitted variable bias: MSAs have local changes that both attract immigrants and boost entrepreneurship. Table 2 presents our regression analysis using a shift-share (Bartik) instrument, which is an approach widely used in the literature for regional studies (31, 32). For example, recent work on the topic of immigration use shift-share instruments to isolate endogeneity driven by host location properties (33).

Our approach takes advantage of changes in migration across industries to other U.S. MSAs and the initial distribution of industries across MSAs to infer changes in potential immigration that are uncorrelated to the focal MSA. More concretely, the idea of the shift-share instrument is that the number of skilled immigrants coming to, for example, the New York-Northern New Jersey-Long Island, NY-NJ-PA MSA, is partially influenced by the nationwide demand for immigrants in the industries that have a presence in New York. Therefore, we can use immigration trends in other MSAs with similar industries, like the Los Angeles-Long Beach-Anaheim, CA MSA, to understand the demand for immigration across the United States in New York's industries, independent of what is happening in New York. This allows us to separate the nationwide demand for immigrants from the specific factors attracting them to New York, and ensures that unobserved aspects of the local business environment that both attract high-skilled immigrants and boost regional entrepreneurship do not bias our analysis. The shift-share approach, explained in our *Empirical Specification*, formalizes this idea across all industries and MSAs, providing an instrumental variable of predicted H-1Bs for each MSA.

We begin by validating our shift-share instrument following methods in shift-share design established in the literature (32). Table 2, Model 1 is a test of the exclusion restriction. This test compares, for each industry in each MSA, whether the number of immigrants to an industry arriving to *other MSAs* correlates to the base level of immigrants in the focal MSA. The exclusion restriction requires that these two are not correlated. This is the case in the data: The coefficient we estimate is small in magnitude and not significant.

Table 2. Two-stage least squares regression models of high-skilled migration on regional entrepreneurship with Bartik instrumental variable

	Dependent variable:		
	Ind. share in 2010	Log (New H-1Bs)	Log (RECPI[t = 0, 1, 2])
	Inst. validation	*First-stage*	*Bartik 2SLS*
	(1)	(2)	(3)
Log(Industry leave out H1-Bs)	−0.0001		
	(0.0001)		
Log(Predicted new H-1Bs)		0.785***	
		(0.033)	
Log(New H-1Bs)			0.060***
			(0.014)
Log(RECPI 2 y ago)		0.140**	0.773***
		(0.059)	(0.040)
Foreign born population percentage		0.393	0.178
		(0.744)	(0.215)
Log(Population)		0.173**	0.177***
		(0.077)	(0.039)
State F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
First stage F-statistic			19.24
Observations	38,520	1,526	1,526
R^2	0.053	0.909	0.977

This table reports our shift-share instrument of H-1B immigration on regional entrepreneurship. Column 1 confirms the instrument test from Goldsmith-Pinkham et al.—the industry share in a region and the leave-out immigration level are uncorrelated (32) Column 2 uses the instrument, the inner product of shares and leave-out industry estimates, to create Predicted New H-1Bs, independent of local shocks. Column 3 presents the main 2SLS estimate. The first-stage F-statistic is 19, indicating a strong instrument. SEs are clustered by MSA. Significance: denoted as $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Model 2 is the first-stage regression. The instrument, Predicted New H-1Bs, represents the number of predicted migrants based on national changes in industry trends (leaving out the focal MSA). There is a strong correlation between our predicted H-1Bs instrument and the actual number of H-1Bs arriving in an MSA. The coefficient is 0.785 and significant at the 1% level. Moreover, the model's F-statistic is 19.24, suggesting that we have a strong instrument.

Model 3 is our two-stage least squares (2SLS) estimate. The coefficient of Log(New H-1Bs) is 0.060 and statistically significant at the $P < 0.01$ level. These results are consistent with an interpretation that there is a relationship between high-skilled immigration and regional entrepreneurship that is independent of features of a region that might simultaneously affect both variables.

Economic significance. The models above provide evidence of a positive statistically significant relationship between high-skilled immigration and regional entrepreneurship. We now consider its economic significance.

Our estimates suggest that a doubling of skilled immigration would predict an increase in entrepreneurship from 4.6% to 7.4%. This estimate is comparable to other effects in the literature. In the case of other government policies, this increase in entrepreneurship is similar, for example, to the 8% increase in entrepreneurship observed after the introduction of state-level research and development tax credits (34). In research on gender, Zandberg showed that increasing access to abortion by one SD leads to a corresponding 5.9% increase in entrepreneurship among women (35). Finally, on technological change, Barrios et al. estimate that the availability of ride-sharing services led to a 3% to 6% increase in entrepreneurial activity (36). However, it may not be clear how this effect translates either to realistic changes in the magnitude of skilled immigration across MSAs or to these MSA's economic outcomes. We present analyses on both of these dimensions below.

First, consider the magnitude of our effect. A key feature of the demand for immigration in the United States is that it is geographically skewed. Out of about 85,000 new H-1Bs into the United States, per year, during our period, an average of 17,857 went to the New York-Northern New Jersey-Long Island NY-NJ-PA, MSA, and 6,644 went to the San Jose-Sunnyvale-Santa Clara MSA. However, only about 500 were awarded to midsize MSAs such as Kansas City, MO-KS, Phoenix-Mesa-Scottsdale, AZ, or Denver-Aurora, CO, and about 20 or less to smaller MSAs like Atlantic City, NJ, and Mobile, AL. Given these differences in the number of skilled immigrants arriving to different regions, reasonable changes in the number of immigrants arriving in a region may have a substantial impact on the region's economic activity outside of superstar MSAs. For example, while an additional 50 high-skilled immigrants in one year would represent only a 0.8% increase in San Jose (and a 0.3% increase in New York), it would be an increase of almost 10% for the Denver MSA and even nearly 200% for Mobile, AL. Based on our estimates, this additional immigration predicts a boost of nearly 12% in entrepreneurship in Mobile, AL in the next three years. Given that, for example, tech employers such as Google and Apple hired 844 and 531 new H-1B workers in 2015, these magnitudes are well within plausible changes regions may experience.

Two, there is an additional economic benefit from regional entrepreneurship that follows high-skilled immigration. In essence, because entrepreneurship is a driver of economic growth (11), then this additional economic activity would improve both regional Gross Domestic Product (GDP) and the tax base. To provide a back-of-the-envelope estimate of this effect, we proceed in several steps. First, we obtain the real GDP (2017 dollars) for each MSA from the Bureau of Economic Analysis and estimate MSA growth rate from 2020 to 2022. The idea is to understand how much this growth rate of GDP can increase thanks to additional entrepreneurship. Then, we use estimates from Guzman and Stern (29) who estimate in impulse-response models an elasticity from entrepreneurship to the GDP growth rate of 0.04. Using our main estimate from Table 2 showing that new H-1Bs predict increases of entrepreneurship by 0.06, this implies that a doubling of H-1B immigrants to a region would also predict higher GDP growth rate by $0.04 \times 0.06 = 0.00024$. We scale this effect by the share of immigrants represented by 500 new arrivals (e.g., for New York, this would be $500/17,857$) and add it on top of the ongoing GDP growth rate of the MSA. Finally, to account for the fact that benefits accrue over time, we extend this over ten years and linearly reduce our contribution to the growth rate from years 7 to 10 by 25 percent each year. We then compare these GDP projections with the projections without immigration to understand the additional GDP created by the new H-1B arrivals, and sum the total over ten years.

If we consider our evidence, together, as a causal effect, it would imply that in a region like Kansas City, MO-KS MSA, 500 additional immigrants would lead to an additional GDP contribution of $280 million over ten years through the new entrepreneurship created, independent of the direct wages paid to the skilled immigrants themselves. Based on tax-to-GDP estimates from the Organization for Economic Co-operation and Development (OECD), this implies $78 million in direct additional taxes to the MSA. The effects are comparable in regions like New York since, although it has many more H-1B migrants (with 500 representing an increase of only 3%), it also has a much larger GDP. 500 new H-1B migrants to New York add an additional $111 million in economic activity and a total of $30 million in additional taxes. These estimates represent only the ecosystem entrepreneurship effects, which means that they are on top of the significant tax and economic growth created by immigrants in their own jobs. If we use the average wage of H-1B immigrants of $116,000 to compare each two, the size of the entrepreneurship effect is substantial, providing an additional 19% of taxes beyond immigrants' wages. We provide the calculations behind these estimates from above in our *SI Appendix*.

From a policy perspective, these benefits are particularly compelling because attracting high-skilled immigrants to fill local labor market gaps is a relatively straightforward policy that does not require significant additional public investments. In contrast to typical tax incentives or to infrastructure costs, immigration does not impose local costs on the government. Yet, as our analysis shows, it can lead to large increases in the local tax base.

2. The Effect of High-Skilled Immigration on Regional Entrepreneurship Accumulates Over Time. Next, we consider how our effect changes over time. In Fig. 1 (see *SI Appendix*, Table S3 for OLS estimates), we report an event study specification at the quarterly level. We note two distinct takeaways.

First, there are no pretrends in our estimates. The correlation between the H-1Bs received by a region and entrepreneurship occurring in the past is the same as the baseline period $q = 0$. This absence of pretrends gives us confidence that our estimates are not driven by changes co-occurring in the region receiving the immigrants or through reverse causality—i.e., changes in regional entrepreneurship itself that predict immigration in the future.

Second, the immediate impact of skilled immigration on entrepreneurship is not statistically distinct from zero. In contrast, the correlation turns positive for entrepreneurship occurring after the skilled migrants arrive. The magnitude is relatively small initially but increases over time. Two years after the immigration event, the coefficient is about 0.14 and statistically significant at the $P < 0.05$ level. In other words, eight quarters later, a 20% increase in skilled immigration is associated with an increase of 2.8% in entrepreneurship. Importantly, these estimates consider the first three years from migration, representing years that virtually all H-1B immigrants have not yet transitioned to permanent residency status, which in principle, would legally permit them to start ventures. Therefore, our results are best interpreted as an indirect effect of skilled immigration on regional entrepreneurship, accumulating over time.

3. The Relationship Is Driven by the Arrival of High-Skilled Immigrants As Distinct from Other Immigrant Categories.

Continuing H-1B visas and MSA entrepreneurship. We proceed to assess the relationship of regional entrepreneurship with other types of immigration activity that do not themselves represent the arrival of high-skilled immigrants. This allows us to further understand whether some alternative mechanisms, such as the demand for skilled labor in a locality or the arrival of immigrants as a whole (independent of whether they are highly skilled) may play a role in the effects we document.

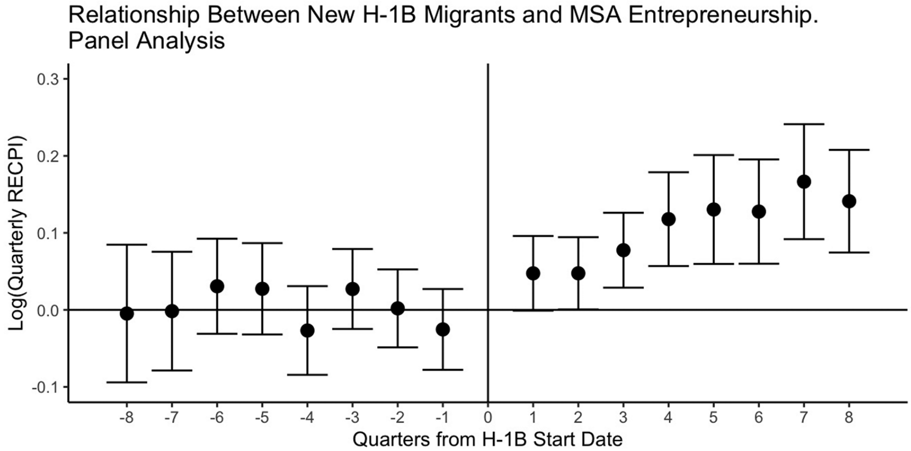

Fig. 1. Correlation between new H-1B immigration and entrepreneurship in panel model. This figure reports the OLS estimates from predicting quarterly RECPI (logged) at quarter q = 0 as a function of the estimated number of new H-1Bs (logged) across quarters q = −8 to q = 8 at the MSA level, where q = 0 is the estimated first quarter of employment of an H-1B employee. We include year and quarter fixed effects. SEs are clustered at MSA. Vertical bars indicate 95% CIs. *SI Appendix*, Table S3 reports the model in tabular format.

Fig. 2 replicates our event study using continuing H-1Bs (see *SI Appendix*, Table S4 for OLS estimates). These visas, by and large, represent skilled immigrants who are already in a region, and are staying in their current role with their current employer or changing jobs, either with their current employer or with a different employer. Therefore, continuing H-1Bs represent the demand for skilled immigrant labor but do not measure the arrival of new immigrants to that locality.

In contrast to Fig. 1, the coefficients in Fig. 2 are flatter and appear to have some pretrends. If anything, entrepreneurship leads the positive effect of continuing H-1Bs. Because immigrants on continuing H-1B visas face the same economic conditions as those on new H-1B visas, but have no effect on entrepreneurship, this suggests that the arrival of new immigrants, in particular, motivates regional entrepreneurship.

SI Appendix, Table S5, also reports MSA-level regressions that include both new and continuing H-1Bs together. The coefficient for new H-1Bs remains positive and significant, and the coefficient for continuing H-1Bs is smaller and not significant.

H-2B visas and MSA entrepreneurship. We next turn to a different type of immigration: low-skilled immigrants. So far, our narrative has suggested that skilled immigration predicts future increases in regional entrepreneurship. An intuitive alternative hypothesis is that the effects are not driven by skilled immigration per se, but rather by any immigration, since immigrants both bring new sources of demand and population growth to a region. First, we emphasize that a demand effect is unlikely to empirically be the case for H-1B migrants, because they represent a tiny portion of any population growth of regions. However, if H-1B immigration is a proxy for broader immigration of any type, then it is possible that the relationship we observe simply reflects changes brought about by overall immigration trends.

Table 3 examines this possibility through H-2B visas. H-2Bs differ from H-1Bs in that H-2Bs are temporary nonagricultural work visas (such as seasonal and service workers) that do not focus on skilled occupations. If our effects are specifically driven by skilled immigration, we should observe no effects from variation in H-2Bs.

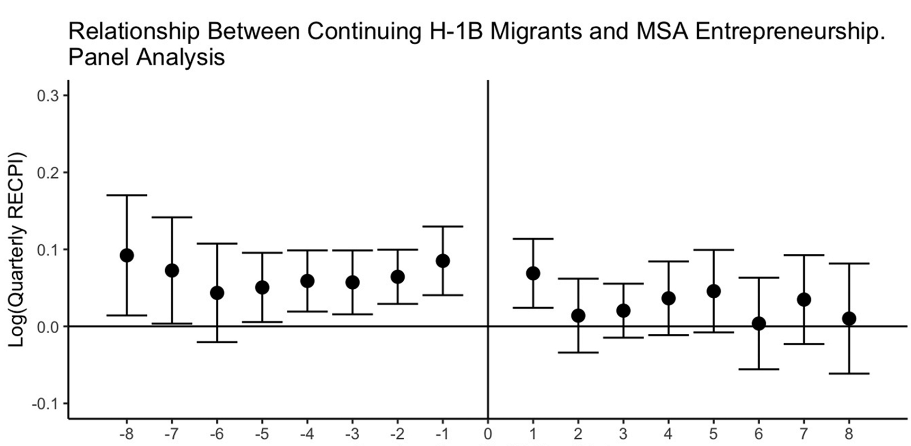

Fig. 2. Correlation between continuing H-1B immigration and entrepreneurship in panel model. This figure reports the OLS estimates from predicting quarterly RECPI (logged) at quarter q = 0 as a function of the estimated number of continuing H-1Bs (logged) across quarters q = −8 to q = 8 at the MSA level, where t = 0 is the estimated first quarter of employment of an H-1B employee. We include year and quarter fixed effects. SEs are clustered at MSA. Vertical bars indicate 95% CIs. *SI Appendix*, Table S4 reports the model in tabular format.

Table 3. OLS regression models of regional entrepreneurship on low-skilled migration (H2-B visas)

	Dependent variable:		
	Log(RECPI[t=0,1,2])		
			Only H-2B > 0
	(1)	(2)	(3)
Log(New H-1Bs)	0.042***	0.043***	0.032***
	(0.010)	(0.010)	(0.011)
Log(Certified H-2Bs + 1)	0.017**	0.006	−0.00000
	(0.007)	(0.011)	(0.010)
Log(RECPI 2 y ago)	0.782***	0.780***	0.814***
	(0.039)	(0.039)	(0.035)
Zero H-2Bs	0.032	0.011	
	(0.031)	(0.036)	
Foreign born population percentage	0.155	0.131	0.139
	(0.243)	(0.244)	(0.221)
Log(Population)	0.175***	0.171***	0.147***
	(0.038)	(0.038)	(0.033)
Log(New H-1Bs) X Log (Certified H-2Bs + 1)		0.003	0.003
		(0.002)	(0.002)
State F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	1,552	1,552	1,089
R^2	0.977	0.977	0.985

This table shows the effect of new H-1B and H-2B workers at year t = 0 on the 3-y cumulative RECPI at the MSA level. Since several MSAs report no certified H-2B applications, the independent variable is H-2Bs + 1 (log-transformed), and we include a dummy variable, Zero H-2Bs, equal to 1 for locations with 0 H-2Bs in a given year. Log(Certified H-2Bs + 1) is mean-centered. In column 3, we focus only on MSAs with at least 1 H-2B worker. SEs are clustered by MSA. Significance denoted as $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Models 1 through 3 in Table 3 use the MSA as the level of analysis. Since there are fewer H-2Bs than H-1Bs, we focus on H-2Bs plus one and add an indicator for having zero H-2Bs to account for the discontinuity at zero. The coefficient for H-2Bs in Model 1 is smaller than others, while the coefficient for H-1Bs does not change. Furthermore, in Model 2, the coefficient of the interaction term between H-1Bs and H2-Bs is close to zero and not significant, which suggests that there are few complementarities between both types of migration. In Model 3, which repeats the same regression but only for those MSAs with a positive number of H-2Bs, the same coefficients are virtually unchanged. We further validate these results in *SI Appendix*, Table S13, where we report the same analysis at the ZIP code level.

We conclude from *SI Appendix*, Table S3 that migration does not appear to predict regional entrepreneurship when it does not carry a skilled component.

4. Our Effect Is Stronger in Conational Immigrant Enclaves, Consistent with a Role of Knowledge Transfer through Relational Embeddedness. We now move to consider the mechanisms. There are two central ways in which high-skilled migrants may improve regional entrepreneurship. First, they provide direct labor to startups through their involvement as founders or early employees (9). Second, they may also contribute to regional entrepreneurship indirectly through knowledge transfer, i.e., through sharing their knowledge and ideas with fellow coworkers or personal ties (e.g., see refs. 37–39). In this case, the way they shape local knowledge flows, local networks, and local talent can by itself lead to changes in firm formation (2, 18).

In what follows, we provide evidence consistent with a knowledge transfer-based mechanism stemming from relational embeddedness, which refers to effects that result from preexisting cohesive social ties between people (21–23). First, we report that the estimate of high-skilled immigration and entrepreneurship is stronger in MSAs with larger concentrations of conational immigrant enclaves. Second, we also observe that when only considering the inflow of high-skilled immigrants into positions at large established firms that would not be considered startups, there is a positive impact on regional entrepreneurship, whereas the effect is much weaker for small firms that are likely to be startups. Both of these results are consistent with a knowledge transfer mechanism.[‡] We review each one.

The moderating effect of immigrant enclaves. New immigrants are more likely to share their ideas and knowledge in areas with other coethnic or conational immigrants because these communities provide a sense of familiarity and trust, rooted in shared cultural, linguistic, and social backgrounds (4, 25, 40). The presence of immigrant enclaves—or concentrations of immigrants from the same country in a given region—can make communication more effective and reduce cultural barriers to knowledge sharing for those who are members of the enclave. Newly arrived immigrants to a region often form social ties with conationals who compose an enclave with the intention of becoming part of a local community. Therefore, if knowledge transfer plays an important role in explaining the positive relationship between skilled migration and entrepreneurship, we expect the positive effect of skilled migration on regional entrepreneurship to be stronger in MSAs with higher concentrations of individuals of the same nationality to the migrants.

In Table 4, we adjust our model of Table 1 to study how differences in the density of different nationalities at the destination regions moderate our effect. Model 1 includes an interaction term between Log(New H-1Bs) and the percent of people living in an MSA who are foreign-born. This interaction term is positive and significant. Models 2 to 4 focus more concretely on conationals. To do so, we estimate the number of H-1Bs that were allotted to Indian citizens (see *New H-1B Visas Awarded to Indian Citizens* for details) and the percent of an MSA's population that is Indian-, Chinese-, Japanese-, and Israeli-born.[§] An ethnic enclaves hypothesis would predict the presence of immigrant conationals facilitates greater regional entrepreneurship through knowledge transfer, making the effect of Indian H-1Bs stronger when they move to MSAs with a larger share of residents who were born in India. On the other hand, the presence of locals from other countries, such as China, Japan, and Israel, should not play a significant role in a coethnic mechanism. This is exactly what we find. The positive effect of incoming H-1B workers who are Indian citizens is more substantial in MSAs with a larger share of locals born in India (model 2), but is not affected by the percent of locals born in China (model 3), Japan (model 4), or Israel (model 3).

Additional evidence on the role of a knowledge transfer mechanism. We next consider additional analyses that help adjudicate the importance of the two potential mechanisms we mentioned, knowledge transfer and labor, in understanding how high-skilled immigration increase regional entrepreneurship.

Our first analysis focuses on the size of firms. Small firms are more likely to be startups that are themselves hiring immigrants and, in consequence, growing faster. Larger firms in our sample are unlikely to be startups. That is, migrants in larger firms

[‡]We do not intend to completely rule out other potential mechanisms, or claim that knowledge and labor are the only potential two, but instead our goal is to simply rule in the role of knowledge transfer as playing an important role in explaining our estimates.

[§]We choose Indian citizen for this analysis since 70% of H-1B are awarded to Indian citizens in our sample. Therefore, the subset of Indian H-1B visa workers allows for meaningful levels of variation in our MSA-year sample.

Table 4. OLS regression models of regional entrepreneurship, assessing potential mechanism: Ethnic enclaves

	Dependent variable:				
	Log(RECPI[t = 0, 1, 2])				
	(1)	(2)	(3)	(4)	(5)
Log(New H-1Bs)	0.041*** (0.010)	0.031 (0.021)	0.005 (0.023)	0.011 (0.021)	0.015 (0.020)
Log(New H-1Bs) X foreign born population percentage	0.148*** (0.041)				
Log(Indians citizens with New H-1Bs) X % population born in India		1.247* (0.647)			
Log(Indians citizens with New H-1Bs) X % population born in China			0.071 (0.622)		
Log(Indians citizens with New H-1Bs) X % population born in Japan				0.575 (4.719)	
Log(Indians citizens with New H-1Bs) X % population born in Israel					−10.770 (9.165)
Log(Indian citizens with New H-1Bs)		0.021 (0.022)	0.033 (0.022)	0.030 (0.022)	0.027 (0.021)
% Population born in India		−0.801 (2.837)	−1.183 (2.190)	−1.180 (2.390)	2.221 (2.185)
% Population born in China			7.140** (3.371)		
% Population born in Japan				77.970*** (19.444)	
% Population born in Israel					230.038*** (47.209)
Log(RECPI 2 y ago)	0.773*** (0.040)	0.765*** (0.049)	0.754*** (0.050)	0.754*** (0.050)	0.743*** (0.050)
Foreign born population percentage	−0.475 (0.306)	0.355 (0.256)	0.275 (0.256)	0.282 (0.262)	−0.052 (0.278)
Log(Population)	0.200*** (0.040)	0.186*** (0.047)	0.216*** (0.050)	0.211*** (0.048)	0.221*** (0.049)
State F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	1,552	1,088	1,088	1,088	1,088
R^2	0.977	0.979	0.979	0.979	0.979

This table examines the moderating effect of immigrant enclaves. Model 1 examines the effect of the percent of the foreign-born population at t = 0 (mean-centered) in an MSA and its interaction with the number of new H-1B workers on regional entrepreneurship. Columns 2 to 5 interact the estimated number of H-1B visas awarded to Indian citizens with the percent of the population from India, China, Japan, and Israel respectively. SEs are clustered by MSA. Significance: $^{*}P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$.

usually cannot contribute to growth in entrepreneurship through their workplace contributions to their employer. Therefore, we anticipate that if increases in H-1B migrants working in larger firms are associated with greater regional entrepreneurship, a plausible explanation is that these immigrants share knowledge, ideas, and resources outside of their employers that reach the regional entrepreneurial ecosystem. We classify firms as large or small firms based on the total number of H-1B visas awarded to them. We consider small firms as those that only get one or two H-1Bs in our period, representing 76% of firms, and large firms as those getting at least 16 visas, representing the top 5% of firms with most applications (see *Data and Methods* for details). *SI Appendix*, Table S6 reports our results: The positive effect increases with the share of immigrants to large firms in an MSA, but not to small ones. We interpret this as suggestive evidence that the knowledge transfer effects are important.

While this analysis studied the initial firm petitioning the visa, there is still a possibility that immigrants move to smaller startups once in the region. If an H-1B worker tends to move to or remain in a startup, the labor effects would be important. On the other hand, if they change roles within or move to large firm, their impact on entrepreneurship would mainly be attributable to their knowledge-based interactions. That is, if shifts in the arrival of H-1Bs lead to subsequent shifts in the number of continuing H-1Bs received by large firms rather than small firms, this again would be evidence consistent with a knowledge transfer mechanism.

To examine this, we use data on continuing H-1B applications,[¶] and split firms hiring continuing H-1B workers into large and small firms (see *Data and Methods* for details). Columns 3 and 4 of *SI Appendix*, Table S6 show that an increase in the number of new H-1B migrants in year t = 0 is associated with a nearly a six times larger increase in the number of continuing H-1Bs received by large firms compared to small firms.

Finally, we report a more exploratory analysis in *SI Appendix*, Table S7, where we separate the quality and the quantity of entrepreneurship in a region. An effect driven by knowledge spillovers is more likely to improve the quality of entrepreneurship by changing the growth orientation of startups, through

[¶]The DOL does not split continuing H-1Bs awarded by whether awardees were simply renewing their H-1B visas for the same role in the same company, or were changing jobs. However, starting 2017, LCA applications data started reporting this breakdown. Using 2017 to 2019 data, we find that only 30% of continuing H-1B applications were filed for employees renewing their H-1B visas.

channels such as the sharing of innovative practices, market access ideas and solutions, and relational capital improving access to financing. In contrast, the role of the workers themselves arriving at a region would also increase the supply of talent in the region, and would therefore have an impact on both the quality and quantity of firms. The effect on quality on our analyses is nearly three times larger than that on quantity suggesting an important role for knowledge spillovers. Furthermore, in *SI Appendix*, Table S12, when we look at differences within individual neighborhoods, we also observe positive effects, even though only knowledge spillovers but not labor markets are typically considered to operate at the neighborhood level.

Robustness

Effect of Superstar MSAs. A potential concern is that our results are driven by superstar entrepreneurial regions like Silicon Valley, which both employ a high number of workers on an H-1B visa, and also have a large number of startups. In this case, rather than documenting a general effect of regions and immigration, we would be documenting just one local, yet highly influential, effect. We address this in *SI Appendix*, Table S8, comparing the effect of H-1B migrants across three groups of MSAs: 1) High startup regions (New York–Northern New Jersey–Long Island, San Francisco–Oakland–Fremont, San Jose–Sunnyvale–Santa Clara, and Boston–Cambridge–Quincy) that also account for 40% of H-1Bs in our sample, 2) Moderate startup regions (Atlanta–Sandy Springs–Marietta, Dallas–Fort Worth–Arlington, Houston–Sugar Land–Baytown, Philadelphia–Camden–Wilmington, and Washington–Arlington–Alexandria), accounting for 21% of H-1Bs, 3) Remaining MSAs in our sample. The coefficient for Log(New H-1Bs) in model 3, excluding the large MSAs, is almost identical to its coefficient in Table 1 model 2, suggesting our results are not driven solely by MSAs highly active in petitioning for high-skilled immigrants.

Effect of Local Financial Capital. Another possibility is that our results, rather than explaining entrepreneurship in a region, are simply a capital effect. For example, our effect may be completely moderated by the presence of venture capital, which would mean that financing, rather than new firms starts, would have been a more central outcome to write our paper around. To study this possibility, in *SI Appendix*, Table S9, we interact several measures of regional venture capital with immigration. Columns 1 and 2 examine the moderating effect of the number of venture capital deals and the amount of venture capital investments in a region respectively. The coefficient of the interaction effect is not significant in Model 1. It is close to zero and only marginally significant in Model 2. Columns 3 and 4 consider the level of individual investments made in an MSA, with similar results. While immigration may have a significant effect on capital (41), this capital effect does not appear to be a significant determinant of the way skilled migration leads to regional entrepreneurship.

Other Regional Factors, Including Education, Innovation, Population Size, Local Wages, and Underlying Regional Entrepreneurship. A third concern is that the relationship is driven by the correlation of immigration to other underlying variables such as regional differences in education, innovation, H-1B worker wages, and quantity and quality of startups. We consider this possibility by performing, for each of these alternative explanations, a split sample analysis—MSAs in the top 50% of the distribution on average between 2012 to 2016, and those in the bottom 50%. We then run our shift-share model on each half of the sample for each of these regional characteristics. *SI Appendix*, Fig. S1 reports the coefficient of Log(New H-1Bs) for each of these regressions. We find that the difference between the split sample pairs for percent with a Bachelor's degree, number of utility patents,[#] population size, and SFR two years ago are not statistically significantly different. While the coefficient size is significantly higher for regions with higher average prevailing wage of H-1B workers and for regions with low RECPI, the general direction of the coefficient is positive.

Founders Being Petitioned by Their Own Startups. Finally, it is possible that our results are not driven by a knowledge mechanism but instead that some founders may be minority (rather than majority) shareholders in corporations and work there as initial employees. This is the case when, under some conditions, the founder's startup is able to sponsor the H-1B visa of the founders themselves, as employees. We examine this concern in two ways.

First, while H-1B data do not allow us to observe whether new employees have shares of a firm, green card application data [Permanent Employment Certifications (PERMs), see *Data and Methods*] do include it for green cards sponsored through an employer. For H-1B visa holders transitioning to green card through their employer, only 0.1% have a reported interest in the sponsoring company, suggesting the incidence of this phenomenon is low.

Second, the concern above only applies for startups that are corporations, since a corporation is the only corporate form that allows appropriate separation between the legal personhood of the firm and its shareholders. Therefore, in *SI Appendix*, Table S10, we separate our instrumental variables analysis by considering regional entrepreneurship separately for corporations and noncorporations, which are limited liability companies (LLCs) and limited partnerships. We find a positive and significant effect even for noncorporations.

Discussion

The direct role of high-skilled immigration on entrepreneurship is well documented (1–12). These studies quantify how immigrants directly contribute to entrepreneurship via firm-level mechanisms such as founding firms or impacting startup performance as employees (42). Our paper complements this literature by expanding beyond firms to isolate a positive relationship between high-skilled immigration and entrepreneurship at the regional level, taking place indirectly. We present complementary evidence consistent with knowledge transfer being a central mechanism for this indirect effect.

While several positive effects of immigration on entrepreneurship have been documented in the literature (see ref. 3 for review), prior literature has also argued that immigrant workers—and skilled immigrant workers, in particular—tend to intensify labor market competition, sometimes crowding out talent from nonimmigrant workers (14, 15). In this case, rather than expanding the talent pool for a given region, native talent is simply replaced with immigrant talent. Therefore, it is possible that although firms that hire skilled immigrants might benefit individually, the skilled immigration into a region might not predict a follow-on higher collective incidence of entrepreneurial ventures.

Our paper attempts to address this debate by being the first, to our knowledge, to report a series of complementary analyses that together suggest a positive relationship between high-skilled immigration and regional entrepreneurship. This includes a shift-share instrumental variables approach, event

[#] About 90% of the patents they issue are utility patents.

study comparing the effect of new versus continuing H-1B visas, and a placebo test with H-2B visas. We find that this relationship is economically important—back-of-the-envelope calculations suggest that the addition of only 500 H-1B migrants can have large spillover effects for both large and midsize MSAs. Moreover, the relationship is stronger when immigrants migrate to localities with a larger share of immigrants from their own country of origin, supporting a mechanism of 'immigrant enclaves' (4, 25, 27, 40)—groups of immigrants supporting each other, cultivating social capital, and facilitating knowledge transfer. We also report additional analyses supporting such knowledge spillover-based explanation for our main effect.

Our study builds on a large literature underscoring the key role of immigrants as conduits of valuable knowledge and information (16, 38). Considering more closely the process of knowledge transfer and how it is moderated by immigrant enclaves, we believe our effect is more concretely explained through relational embeddedness. Relational embeddedness situates new immigrants into communities characterized by cohesive ties between conationals within the regions in which they live. These ties are characterized by cultural familiarity and high interpersonal trust, which can facilitate the transfer of complex and tacit knowledge (43–45).

However, a limitation of our study is that we do not provide direct evidence of knowledge transfer. We therefore encourage future research to seek this evidence using more granular employee-firm data. Such granular data can also enable researchers to develop alternative shift-share instruments based on immigrants' ethnicity or country of origin (8). In addition, our H-1B data lack sufficient variation in migrants' nationalities, with 70% being Indian. This limits our ability to expand the enclave analyses to H-1B immigrants from other countries—even though a more detailed enclave analysis should study many countries at a time. We encourage future research on the generalizability of our enclave analyses. Finally, we are also limited by the length of our panel. Our analysis examines entrepreneurial quality summed over three years. The longer-term implications of (i.e., beyond 3 y) regional entrepreneurship following changes in a high-skilled immigration is an avenue for future research.

There are several other additional avenues for follow-on research. First, related to mechanisms, we recognize there is substantial additional research to be done to fully disentangle all potential processes that may explain the relationship we uncover. While we focus on providing evidence consistent with a knowledge transfer mechanism, there are several other ways in which immigrants could improve regional entrepreneurship. Further research examining these additional pathways will be valuable. We also hope this study lays the groundwork for future research to further explore the interplay between selection and causal effects of high-skilled immigration. Our goal in this study was to isolate the treatment and present evidence for a plausible causal interpretation, not to dismiss the importance of selection. While our analyses suggest the possibility of a causal relationship between high-skilled immigration and regional entrepreneurship, selection likely plays a role too. Finally, another important question emerging from our research is understanding the specific type of knowledge being transmitted by high-skilled immigrants. For example, Kim (46) finds that following a startup's acquisition, the rate of acquired employees' entrepreneurship significantly increases both within and outside the acquired firms' industry. This suggests that the type of knowledge spillovers can transcend industry boundaries, being not just technical, industry-specific knowledge but also broader tacit knowledge and entrepreneurial know-how. Building on this work, it is crucial to examine whether knowledge transfer from skilled migration is predominantly technical, tacit (e.g. new ideas or know-how on how to start a company), or both. We encourage future research to delve deeper into distinguishing the types of knowledge flows from skilled immigration.

At a broader level, the role of immigration in shaping economies, and the way immigrants contribute to or compete with the native population, is a burgeoning area of research with clear practical implications. Despite a long tradition of research on immigration across the social sciences, our work reveals ample space for new scholarship to explore the ways in which high-skilled migration shapes regional entrepreneurship. We hope our findings not only spark additional research on this very important topic, but that they also inform policy decisions.

Data and Methods

We focus on the relationship between H-1B immigration and regional entrepreneurship at the MSA level. The United States Office of Management and Budget defines Core-based Statistical Areas (CBSAs) as a core area tied to at least one urban area with a population of 10,000 or more. CBSAs are further subdivided into two groups–1) Micropolitan Statistical Areas, which are core areas composed of at least one urban area with a population of 10,000 to 50,000 people; and 2) Metropolitan Statistical Areas, composed of at least one urban area with more than 50,000 inhabitants (47). In supplementary analyses, we also validate our results at the ZIP code level.

We measure skilled immigration using data from the USCIS, which we match to regional entrepreneurship outcomes using the Startup Cartography Project (28). We complement this data with labor applications (for H-1Bs) and permanent residence applications data from the U.S. DOL, regional data from the American Community Survey (ACS), regional financial capital data from Pitchbook, and regional patents data from the U.S. Patent and Trademark Office. We next describe each dataset and our measures.

Data

Startup Cartography Project. We use entrepreneurship data from the SCP (28), a repository of startup formation data from 1988 to 2018, measuring both the quantity and quality of entrepreneurship. The SCP counts business registration records–filings for new corporations, partnerships, or LLCs–and uses information from these records or intellectual property filings to estimate startup quality at founding. Startup quality is the predicted probability of an equity growth event (initial public offering or high-value acquisition) based on founding characteristics like corporation status, short name, Delaware registration, and holding a patent or trademark. These quality estimates meaningfully characterize firm potential. Out-of-sample estimates show 37% of firms that achieve an equity growth event score in the top 1% of the quality distribution, and 54% in the top 5% (28). Employment-based growth outcomes show a similar pattern.

We obtained two measures from SCP for both ZIP Codes and MSAs: the SFR, indicating the quantity of firms, and RECPI, representing the quality-adjusted quantity of firms (quantity times quality). The public data on the SCP website run until 2016. We updated it to include 2017 and 2018, excluding Michigan, South Carolina, Illinois, and Delaware, for which we lack data for these years. We created yearly and quarterly versions of the data for a more fine-grained panel to study pretrends.

Our key variables focus on the total entrepreneurship of a region over three years. Our primary dependent variable, RECPI$[t = 0, 1, 2]$, is the sum of the value of RECPI during the current year and the two subsequent ones. We sum our measures of entrepreneurship over a 3-y period because the potential impact of migration on regional entrepreneurship might take some time to manifest, and likely accumulates over time. We estimate the same measure for SFR as SFR$[t = 0, 1, 2]$, and estimate the quality of startups as the ratio of RECPI over SFR.

Yearly Panel of New and Continuing H-1Bs. We use yearly H-1B data reported by the USCIS for fiscal years 2012 to 2016. USCIS defines fiscal years from Oct. 1 to Sept. 30 of the next year, assigning the fiscal year to the concluding year.[‖] These data, collected from fields on an employer's I-129 form or adjudicative decisions, are publicly available on the USCIS H-1B Employer Data Hub (48).

USCIS reports H-1B petition decisions for two different types of applications: initial H-1Bs and continuing H-1Bs. Initial H-1Bs represent petitions with "New employment" or "New concurrent employment" while continuing H-1Bs include all other H-1B petitions, such as workers receiving certain promotions, changing their employer, or amending petitions.

From these data, we restrict our sample for analysis in two ways. First, we focus only on initial approved H-1Bs to capture the physical arrival of a new immigrant to the United States.[**] Second, we exclude a small number of records related to consulting employers that hire a significant number of H-1Bs, but whose employees are unlikely to reside close to the employer. Examples include Wipro and Tata Consulting, both of which are professional services firms that list only one location in the United States—typically its American headquarters office—but whose employees on H-1B visas are likely to work in branch offices across the country. To do so, we exclude all individual records with over 1,000 initial approved H-1Bs. This represents only 47 records in our data (less than 0.001% of all records). We have approximately 430,000 initial H-1Bs approved with an MSA location in our analysis. Our core measure *New H-1Bs* counts the number of these new H-1Bs for each year in an MSA.[††] Similarly, we also create a second measure *Continuing H-1Bs*. This measure represents the number of continuing H-1Bs by fiscal year and location. There are about 639,000 continuing H-1Bs in an MSA between 2012 and 2016.

Quarterly Panel of New and Continuing H-1Bs. We also develop a quarterly panel by MSA using our data together with certified LCA records. LCAs are documents submitted by H-1B petitioners to receive a certification from DOL that an H-1B will meet specific work requirements. LCAs include the employer's location and the employment start date. However, since the LCA records do not indicate whether the applications were for new or continuing H-1B visas, we split LCA applications based on whether they are new or continuing by using the difference between the LCA application date and the start date. We categorize all LCA applications with less than 30 d as continuing and the rest as new. Using 2017 to 2019 LCA data, which does separate continuing and new applications, we find that 87% of all visas awarded under 30 d are continuing (representing 66% of all continuing visas). In contrast, only 13% of new H-1Bs are under 30 d.[‡‡]

We then estimate, for each MSA, the share of new or continuing LCAs that occur in each quarter. We use this to project the count of H-1Bs (new or continuing) in our data across this distribution and measure new H-1Bs and continuing H-1Bs by quarter, year, and MSA. We also allow this panel to begin in 2010, allowing us to include longer pretrends in our analysis. This is not possible in our main analysis, which uses the year 2010 to estimate the Bartik shares of our instrument. We are also able to include quarterly H-1B count estimates for 2017 and 2018 since our dependent variable does not aggregate entrepreneurship over the next three years in this panel analysis as it does in the cross-section analysis.

Certified H-2Bs. We obtain H-2B data from the DOL Employer Data Hub. H-2Bs are temporary nonagricultural visas that focus on unskilled labor, such as landscaping and groundskeeping (Standard Occupational Classification code 37-3011) or maids and housekeeping cleaners (Standard Occupational Classification code 37-2012), etc. We focus on certified H-2Bs and use the reported year from the certification start date as the year that employment starts.[§§] We have about 442,000 H-2B applications from 2012 to 2016 in our sample, of which 322,000 are in an MSA that also received H-1Bs in that year.

New H-1B Visas Awarded to Indian Citizens. Since H-1B application records do not indicate the applicants' country of origin, we leverage the DOL's fiscal year 2018 to 2022 PERM applications records to estimate it. For a given MSA and year, we calculate the percent of certified PERM applications from H-1B visa recipients who are Indian citizens. In this time frame, Indian H-1B workers accounted for the vast majority of all certified PERM petitions, constituting about 70% of the pool. For each year, we then project the distribution of certified PERM applications from Indian citizens for a given MSA and year on to the total new approved H-1Bs for that MSA 6 y ago to estimate the number of H-1B visas received by Indian natives, Indians Citizens with New H-1Bs. In other words, we match fiscal year 2012 H-1B counts for an MSA with fiscal year 2018 share of Indian certified PERM applicants for the same MSA, and so forth. We assume that *Indians Citizens with New H-1Bs* corresponds to the number of Indian workers migrating to an MSA. We choose a lag period of 6 y because an H-1B visa is valid for a maximum period of 6 y. Hence, we assume that a typical H-1B visa holder receives PERM certification to get in queue for U.S. permanent residency after holding an H-1B visa for 6 y.

Firm Size Classification.

Small versus large firm classification for firms receiving new H-1Bs. Based on the 2012 to 2016 panel data on firms that received new H-1Bs, we define a firm as a small firm if it received one or two new H-1Bs over this period. This covers about 76% of firms in the sample, and 16% of all new H-1B visas that were approved. We then define a firm as a large firm if the firm is in the top 5% of firms in terms of the total number of new H-1Bs approved between 2012 and 2016. This equates to 16 H-1Bs. Large firms calculated as such cover 65% of all new H-1Bs.

Small versus large firm classification for firms receiving continuing H-1Bs. Using 2014 to 2018 panel data[¶¶] on firms that received continuing H-1Bs, we define a firm as a small firm if it received one or two continuing H-1Bs over this period. This covers 69% of firms in the sample, and 10% of all approved continuing H-1B visas. We then define a firm as a large firm if the firm is in the top 5% of firms in terms of the total number of new H-1Bs approved between 2014 and 2018. This equates to 26 continuing H-1Bs. Large firms calculated as such cover 69% of all continuing H-1Bs.[##]

Local Financial Capital. Using Pitchbook data, we count the number and total dollar value of "completed" (e.g. as opposed to "canceled" or "in progress") round 1 and round 2 venture capital investments for each year and MSA, focusing on companies headquartered in the United States. We do the same for investments classified as "individual," expecting, based on text descriptions, most of these to be from angel and other individual investors.

Number of Patents. We obtain yearly 2012 to 2015 utility patent data for each MSA from publicly available records from the U.S. Patent and Trademark Office's (USPTO) website (49). While the USPTO issues several types of patents, about 90% of the patents they issue are utility patents (also known as "patents for invention").

Local Prevailing Wage. We again leverage the DOL's LCA records to calculate the average prevailing wage by year and MSA for each certified LCA petition filed for H-1B workers between 2012 and 2016. 93% of the applications report the annual prevailing wage rate. The remaining 7% report hourly, monthly, biweekly, or weekly wages. We assume a 40 h week for 52 wk and 12 mo in a calendar year to convert these to annual wages.

[‖] Applications and petitions are assigned to a year based on their adjudication date, not their filing date. We assume new immigrants arrive on the calendar year of their corresponding fiscal year, which should correspond to the vast majority of cases.

[**] We do this based on data in the USCIS data hub, which reflect the outcome of the first decision. Subsequent decisions, such as a decision on an appeal or revocation, are possible, though rare.

[††] USCIS data do not differentiate between worksite and employer locations. We use the employer's ZIP Code to infer the employment destination ZIP Code and MSA. A concern is that employer addresses may not match worksite locations well. In a robustness test, we use LCA data from the DOL, which separates worksite and employer locations. We identify employers where at least 90% of visa applications have matching worksite and employer municipality and state, and rerun key model specifications using these employers. Our results remain consistent with this subsample (*SI Appendix*, Table S11).

[‡‡] In unreported analyses, we also confirm that none of our results change meaningfully when we change this threshold to 60 d.

[§§] Using certified applications is different from the H-1B data at the core of our analysis, where we are able to consider the H-1Bs that were actually approved. H-2Bs are not separated into approved or rejected in the DOL data.

[¶¶] We use years 2014 to 2018 since we forward lag continuing H-1B visa count by 2 y.

[##] The DOL does not split continuing H-1Bs awarded by whether awardees were simply renewing their H-1B visas for the same role in the same company, or were changing jobs. However, from 2017, LCA data reported this breakdown. Using 2017 to 2019 data, we find that only 30% of continuing H-1B applications were filed for employees renewing their H-1B visas.

Additional Measures from the American Community Survey. We downloaded additional measures at the MSA and ZIP code level from the U.S. Census ACS (50–52). For MSAs, we include four yearly measures: *Population*, *Foreign Born Population Percentage*, *Percent with a Bachelor's Degree or Higher*, and *Percent of Families with Over $200,000 in Income*. We also use 5-y moving average data to estimate the percent of the total population born in India, China, Japan, or Israel by MSA and year.

Sample

SI Appendix, Table S1 reports summary statistics for our data. Panel A focuses on MSAs. There are 1,552 observations for 321 MSA across 5 y. The average number of H-1Bs arriving at an MSA is 275, though this measure is significantly skewed. The average RECPI is 2.98, again similarly skewed, and the average aggregate three-year RECPI is 9.43. The average number of firms registered in an MSA in three years is 18,050. Panel B reports the summary statistics for ZIP Code data. Panel C does so for our quarterly MSA data.

Empirical Specification

Our analysis focuses on two complementary specifications to estimate the relationship between high-skilled immigration and regional entrepreneurship: 1) an event study using MSA panel data with quarterly variation, and 2) a shift-share (Bartik) instrument using immigration to other destinations to instrument for immigration to a region. We review each in detail below.

Preliminary MSA Model.

$$\mathrm{Log}(\mathrm{CumRECPI}_{i,s,t}) = \beta \mathrm{Log}(\text{H-1Bs}_{i,s,t}) + \alpha \mathrm{Log}(\mathrm{RECPI}_{i,s,t-2}) + \zeta' X_{i,s,t} + \delta_s + \gamma_t + \epsilon_{i,s,t}. \quad [1]$$

We first overview our preliminary OLS model at the MSA level. While this model is not at the core of our identification approach, it will be the basis for our other specifications. For each MSA i, in state s, and year t we estimate Eq. **1**, where $\mathrm{CumRECPI}_{i,s,t}$ is the total sum of RECPI occurring in an MSA from year t to $t+2$, *New H-1Bs*$_{i,s,t}$ is the number of H-1B workers arriving to an MSA in year t, $\mathrm{RECPI}_{i,s,t-2}$ is the entrepreneurship occurring in an MSA two years before, $X_{i,s,t}$ is a vector of controls including MSA population and foreign population percentage, δ_s are fixed effects for each individual state and γ_t are fixed effects for each year, and $\epsilon_{i,s,t}$ is an error term clustered at the MSA level.

While we do not take this specification as causal, it does address some key confounders. By including both state and year fixed effects, we compare differences across MSAs in the same geography and across time, rather than across the whole United States.

Shift-Share Instrument. This identification approach uses a shift-share instrument (31, 32), which instruments immigration to an MSA by using the cross-product of the MSA's industry structure and industry-level immigration to other locations. Before describing its implementation, we provide a toy example to elucidate its intuition by considering immigration to the New York MSA.

The demand for skilled immigrants arriving in the New York MSA depends on two distinct sources of variation: local characteristics of New York's industry that influence this demand for immigrants (including local entrepreneurship) and the general demand for immigrants across industries at the national level. Local events in New York may reasonably influence both immigration and new firm formation, creating an omitted variable bias. Our goal is to use the second source of variation, national demand across industries, to capture shifts in immigration that are independent of changes in New York and, therefore, uncorrelated to local entrepreneurship. We do so by taking advantage of the demand for immigration in other locations that are exposed to similar industries as New York. For example, both New York and Los Angeles are highly represented in software and media. Therefore, H-1B immigration to software and media in Los Angeles may predict H-1B arrivals to these industries in New York, independent of local New York changes.

The shift-share approach formalizes this idea across all industries and MSAs. In a similar intuition to the example, the goal is to create, for each MSA, a "replica" MSA estimating the number of immigrants that arrive based on the total immigration for each industry to other locations, imposed onto an MSA's industry shares. Then, we can use this predicted immigration in an instrumental variable framework on the specification from Eq. **1** to estimate the impact of immigration due only to shifts to immigration that are not endogenous to the MSA.

More formally, following ref. 32, we proceed in two steps. First, we estimate the distribution of H-1B immigrants across MSAs for each industry in a prior period. The variable $IndShare_{i,j,2010}$ in Eq. **2** below represents the share of all visas arriving in industry j that belong to MSA i at $t = 2010$, 2 y before our cross-sectional sample begins. Next, for each industry, we measure $\text{H-1Bs}_{-i,j,t}$, which is the number of H-1Bs arriving at t to industry j, and *excluding out the focal MSA*. Finally, our instrument *Predicted H-1B*$_{i,t}$ is the product of $IndShare_{i,j,2010}$ and $\text{H-1Bs}_{-i,j,t}$ aggregated at the MSA level. We focus on sector-level variation (2-digit NAICS) since that is the level of aggregation provided in the USCIS data.

$$\textit{Predicted H-1B}_{i,t} = \sum_j (IndShare_{i,j,2010} * \text{H-1Bs}_{-i,j,t}). \quad [2]$$

We repeat this approach at the ZIP Code level, where we create our instrument by leaving out all ZIP Codes in the MSA of focal ZIP Code. We also exclude all rural areas that do not have an MSA. *SI Appendix*, Table S12 reports our results for the effect of high-skilled immigration on regional entrepreneurship at the ZIP Code level.

Event Study. This approach uses the quarterly panel described earlier, in *Data: Quarterly panel of new and continuing H-1Bs*.

For an MSA i, in quarter q, and year t, we estimate Eq. **3**:

$$\mathrm{Log}(\mathrm{RECPI}_{i,q,t}) = \beta' \ \mathrm{Log}(\text{New H-1Bs}_{i,q,t}) + \gamma_q + \lambda_t + \epsilon_{i,q,t}, \quad [3]$$

where $\mathrm{RECPI}_{i,q,t}$ is RECPI occurring in an MSA in quarter q of year t, and Log(New $\text{H-1Bs}_{i,q,t}$) is a vector of the log of new H-1Bs in that MSA lagged up to eight quarters before and led (forward lag) to eight quarters after. β is a vector with the coefficients of interest, representing the relationship between lagged skilled immigration and regional entrepreneurship. We exclude $t = 0$ and consider it the reference level. γ_q and λ_t are fixed effects for quarter and year, respectively, and $\epsilon_{i,q,t}$ is a SE clustered at the MSA level.

The vector β represents how much more immigration is correlated with entrepreneurship relative to the baseline at $q = 0$. Because we are interested in the relationship of H-1Bs to future (or past) entrepreneurship, we report our coefficients in inverse order. That is, we consider the coefficient with H-1Bs at $q = -4$ to reflect the additional impact of immigration on entrepreneurship four quarters after skilled migrants arrive, and thus it is plotted at $q = 4$. This specification also allows us to test for reverse causality: whether entrepreneurship is related to future immigration changes rather than past changes. In our specification, this would imply that leads of H-1B would have predictive power on RECPI above the baseline. In other words, to rule out reverse causality, we expect that the forward-lagged Log(New $\text{H-1Bs}_{i,q,t}$) variables would not have significant effects on $\mathrm{RECPI}_{i,q,t}$, whereas the backward-lagged Log(New $\text{H-1Bs}_{i,q,t}$) variables would not.

Data, Materials, and Software Availability. We have deposited our datasets and all analysis code to replicate the main result in an Open Science Framework repository (https://osf.io/hrx94/) (53). Given the proprietary and sensitive nature of the Pitchbook data used, we do not publicly release these data. This data can be purchased through Pitchbook.

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