



The role of industry-specific, occupation-specific, and location-specific knowledge in the growth and survival of new firms

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Edited by William B. Rouse, Stevens Institute of Technology, Hoboken, NJ, and accepted by Editorial Board Member Pablo G. Debenedetti July 23, 2018 (received for review February 15, 2018)

How do regions acquire the knowledge they need to diversify their economic activities? How does the migration of workers among firms and industries contribute to the diffusion of that knowledge? Here we measure the industry-, occupation-, and location-specific knowledge carried by workers from one establishment to the next, using a dataset summarizing the individual work history for an entire country. We study pioneer firms—firms operating in an industry that was not present in a region—because the success of pioneers is the basic unit of regional economic diversification. We find that the growth and survival of pioneers increase significantly when their first hires are workers with experience in a related industry and with work experience in the same location, but not with past experience in a related occupation. We compare these results with new firms that are not pioneers and find that industry-specific knowledge is significantly more important for pioneer than for nonpioneer firms. To address endogeneity we use Bartik instruments, which leverage national fluctuations in the demand for an activity as shocks for local labor supply. The instrumental variable estimates support the finding that industry-specific knowledge is a predictor of the survival and growth of pioneer firms. These findings expand our understanding of the micromechanisms underlying regional economic diversification.

economic complexity | knowledge diffusion | economic development | regional diversification | human capital

Can developing countries and cities thrive through their own entrepreneurship, or must they attract external investment? What are the factors that influence the success of local ventures? Development depends on undertaking new tasks, which require knowledge. In this paper, we estimate the impact of a worker's knowledge about an industry, occupation, and location in the survival of pioneer firms (1): firms that start operating in a region where their industry was not present.

Understanding the success of pioneer firms is key to understanding the mechanisms behind industrial diversification. When a pioneer firm succeeds, the region where this firm is now present will have successfully developed a new industry. Here, we use a large administrative dataset with almost complete work histories for all of the individual workers of a country, to measure the knowledge carried by workers from their previous jobs into pioneer firms. This dataset allows us to estimate the industry-specific knowledge, occupation-specific knowledge, formal schooling, and location-specific knowledge that each worker brings into a pioneer firm. We use this fine-grained description to test which type of knowledge matters most for the growth and survival of pioneer firms and compare these results with new firms that are not pioneers: nonpioneer firms.

For decades, human capital has been recognized as an important determinant of economic growth (2–10). But human capital is not just a worker's formal schooling. Workers acquire important skills, knowledge, and contacts at work. A 40-year-old worker

brings, on average, more years of experience into a company than years of schooling. This work experience, which is specific to an industry, a location, and an occupation, should impact the growth and survival of the activities where these workers are involved. The specificity of this knowledge pushes us to think of human capital not only in terms of intensity, but also in terms of relatedness. Workers are not simply knowledgeable or skilled, but possess knowledge that is related to specific activities, even to new activities that have never before been present in a city or a country. In this paper, we test what type of related knowledge is a more critical ingredient in the success of new firms that lead to the development of new industries. While there is a long literature measuring relatedness between products (11, 12), industries (13, 14), technologies (15, 16), and even occupations (17), there is little work separating these relatedness measures into multiple forms of human capital.

In this paper we decompose knowledge into a 2D representation, measuring how related the previous experience of a worker is to the industry and to the occupation of his or her new job. A worker with abundant formal schooling and experience can be classified as someone with little related experience if her work history involves occupations and industries that are unrelated to her current employment. Conversely, a worker with low formal education can be classified as having high related experience if she moves into an industry and occupation that are related to the ones she has performed previously. The dimensions of industry- and occupation-specific knowledge are not necessarily tied together, since a worker can have abundant experience in the occupation of her new job, while having very little experience in a related industry. We test the relative importance of these dimensions of knowledge relatedness for the survival and growth of pioneer firms and compare these results with their relative importance for new firms that are not pioneers.

The idea that workers bring knowledge into the firms they participate in is an idea that has a long tradition in organizational

This paper results from the Arthur M. Sackler Colloquium of the National Academy of Sciences, "Modeling and Visualizing Science and Technology Developments," held December 4–5, 2017, at the Arnold and Mabel Beckman Center of the National Academies of Sciences and Engineering in Irvine, CA. The complete program and video recordings of most presentations are available on the NAS website at www.nasonline.org/modeling-and-visualizing.

Author contributions: C.J.-F., E.L.G., and C.A.H. designed research; C.J.-F. performed research; C.J.-F., B.J., E.L.G., and C.A.H. analyzed data; and C.J.-F., B.J., E.L.G., and C.A.H. wrote the paper.

The authors declare no conflict of interest.

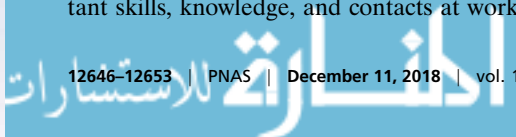
This article is a PNAS Direct Submission. W.B.R. is a guest editor invited by the Editorial Board.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1800475115/-DCSupplemental.

Published online December 10, 2018.



learning. According to Herbert Simon (18), organizations acquire knowledge either by the learning of their members or by ingesting new members. Because a pioneer firm only has new members, the knowledge this firm has needs to come from the workers that it hires. We find that the survival of pioneer firms increases significantly when their first hires are people with industry-specific knowledge and with experience in that location, but not with occupation-specific knowledge. When comparing pioneers with nonpioneers, we find that industry-specific knowledge is significantly more important for pioneers than for nonpioneers and that occupation-specific knowledge plays a relatively more important role for nonpioneers. There are some serious concerns relating to the endogeneity of starting a firm and of hiring. For instance, firms with more social capital may be able to hire more people from related industries. We cannot address these concerns fully, but we can instrument for the number of workers from a related industry available in a labor market by looking at national industrial shifts using a Bartik-style instrument (19). Intuitively, the supply of related workers is higher in areas with related local industries that have received adverse national or global shocks. Our results on the importance of related knowledge are similar when we use this instrument.

Together, our results show how work histories can be used to measure the types of knowledge brought by workers into pioneer firms and also help uncover the relative importance of industry- and occupation-specific knowledge in pioneering economic activities. These results tell us that the success of the pioneering activities that promote diversification depends strongly on the move of local workers with related knowledge into these new activities.

Data

We use Brazil's Annual Social Security Information Report (RAIS) compiled by the Ministry of Labor and Employment (MET) of Brazil between 2002 and 2013. The RAIS dataset uses the National Classification of Economic Activities (CNAE) for industries and the Brazilian Occupations Classification (CBO) for occupations, both revised by the Brazilian Institute of Geography and Statistics (IBGE).

The RAIS dataset covers about 97% of the Brazilian formal labor market (20) and contains fine-grained information about individual workers, including 5,570 municipalities [which are grouped by the IBGE into 558 microregions based on similar productive structure and spatial interaction (21)], 501 occupations, and 284 industries for more than 30 million workers each year. Location information is provided at the discrete level of each municipality, so a continuous treatment is not possible. Municipalities in Brazil are grouped by IBGE into microregions based on similar productive structure and spatial interaction

(21). Microregions are grouped into 137 mesoregions, which are grouped into 27 states, and states are grouped into 5 macroregions. All of the results presented in the main text use the three-digit level for industries, the four-digit level for occupations, and microregions as the spatial unit of analysis. We use microregions because they provide more stringent criteria than municipalities for identifying pioneer firms; it is easier to be the first firm to operate in an industry inside a small municipality than inside a much larger microregion. *SI Appendix* provides an alternative operational definition of pioneer firms based on microregions plus their neighborhood.

One of the key characteristics of the RAIS that makes it so useful for research is its granularity. The variables in the RAIS can be tracked down to the individual level, which makes it the most important source of information on the formal labor market dynamics in the country. The classification of industries went through a major revision between 2005 and 2006, which we solve by splitting the analysis into before and after 2006.

Unfortunately, a firm that does not declare an RAIS in a particular year may not be necessarily "dead," but just facing economic problems that make it rational not to pay taxes in that year or not to appear in any official control mechanism. In fact, many firms simply freeze their activities, awaiting better economic events. This will lead us to underestimate the survival rate of firms, although the exit from the RAIS is surely itself an important event. Because Brazilian legislation makes it relatively easy to open a company, but relatively difficult to close one, many firms, especially small firms, often close without informing official authorities, suggesting that the exit from the RAIS might be a better expression of a company's status than the official closing of the firm. Studies conducted by the IBGE and MTE estimate that the rate of underreporting of firms' death ranges from 14% to 20% of actually closed firms. To partially address these issues, we consider firms to be dead when they stop reporting for at least 2 consecutive years. Despite these limitations, the RAIS is the main source of information on the rate of firm creation and destruction at the municipal level (20). In fact, the Central Registry of Firms (CEMPRE) is built by the IBGE and MTE based on the information available in the RAIS.

Results

Pioneer firms are the basic units of economic diversification. Here, we define a pioneer firm as a firm that is new (no record of it for at least 6 y) and that operates in an industry that is new to its region (no record of the industry in the region for at least 2 y before the pioneer). For companies starting after 2006 we add the extra condition that they operate for at least 2 consecutive years, to filter out small short-lived firms. Because we need at least 2 y of work history of the pioneer's first hires, and

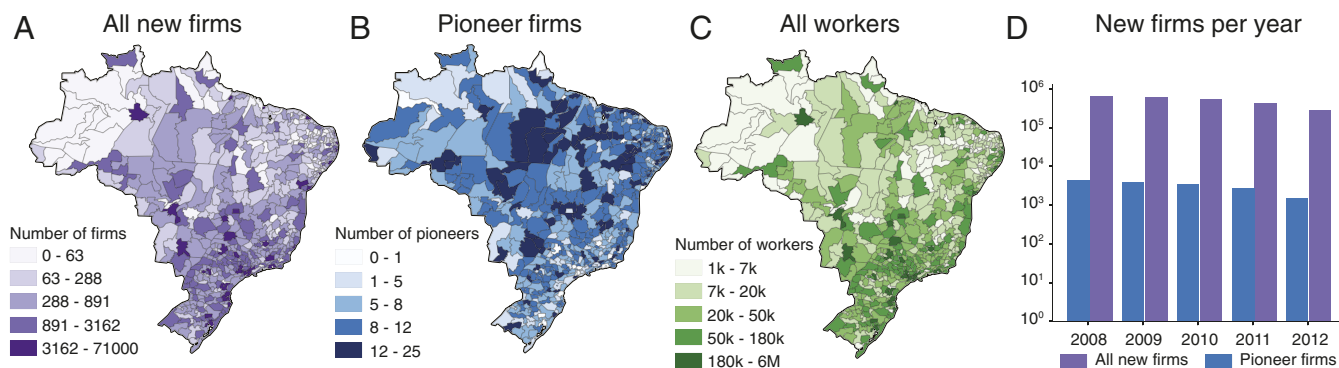


Fig. 1. Spatial distribution of new firms in Brazil created between 2008 and 2012. (A) All firms. (B) Only pioneer firms. (C) Distribution of workers. (D) Number of firms created each year.

because the CNAE went through a major revision between 2005 and 2006, we analyze only firms created either in 2005 or after 2008 (for more information see *SI Appendix*).

Fig. 1 shows the spatial distribution for all new firms (Fig. 1A), pioneer firms (Fig. 1B), and workers (Fig. 1C), across Brazilian microregions between 2008 and 2012. During the observation period, Brazil produced roughly 500,000 new firms per year, of which only about 3,000–4,000 (less than 1%) were pioneers (Fig. 1D). For information about the industries of pioneer firms see *SI Appendix*.

For pioneers, all of their employees are new hires, so all of their initial stock of knowledge is connected to their initial workforce (18). We base our measure of the knowledge brought in by a company's new hire on the industry and the occupation of his or her previous job. Because of the limited time range of the data, we consider only jobs performed during the 2 y before the creation of the pioneer firm. For instance, if a worker was a teller (occupation) for a telecommunication company (industry), we assume that she brings two types of knowledge to the pioneer firm: industry-specific knowledge about the telecommunication industry and occupation-specific knowledge about being a teller. Because different industries and different occupations vary along a continuum, we abandon the view of industry- and occupation-specific knowledge as two binary variables (22). We instead use a continuous approach, building on the literature on relatedness. For example, the industries of shoe manufacturing and shirt manufacturing are different industries, but they are similar enough that a worker moving from shoe manufacturing to shirt manufacturing should be regarded as having some industry-specific knowledge about shirt manufacturing, relative

to workers coming from a less-related industry such as animal agriculture. The diagram presented in Fig. 2A shows a pioneer firm made of three workers: The first and third workers come from the same occupation, but an unrelated industry, and the second one comes from a different occupation, but from a related industry.

To measure the relatedness between the industry of a pioneer firm and the work histories of that firm's workers, we follow the literature on relatedness and use labor flows between pairs of industries at the national level (13, 14). Similarly, we measure relatedness for each pair of occupations by looking at labor flows among occupations across the entire Brazilian economy. Unfortunately, the CBO classification has not been successfully linked to skill compositions, so we cannot use a direct measure of skill similarity. Logically, labor should flow freely between industries and occupations that require similar knowledge and not between industries and occupations that require wildly different knowledge. In fact, the relatedness measure based on labor mobility has been termed "skill relatedness" by some authors (14, 23), because individuals changing jobs will likely remain in activities that value the skills associated with their previous work.

Formally, we define the relatedness between industry i and industry i' as the residual of a regression explaining labor flows as a function of the size of industries and their growth rates (14). That is, we consider a pair of industries (occupations) to be related when the labor flows between them are higher than what we would expect based on the size and growth of a pair of industries. In other words, we take the residuals of the regression from Eq. 1, where $F_{i \leftrightarrow i'}^{(t)}$ is the total flow of workers in log-scale

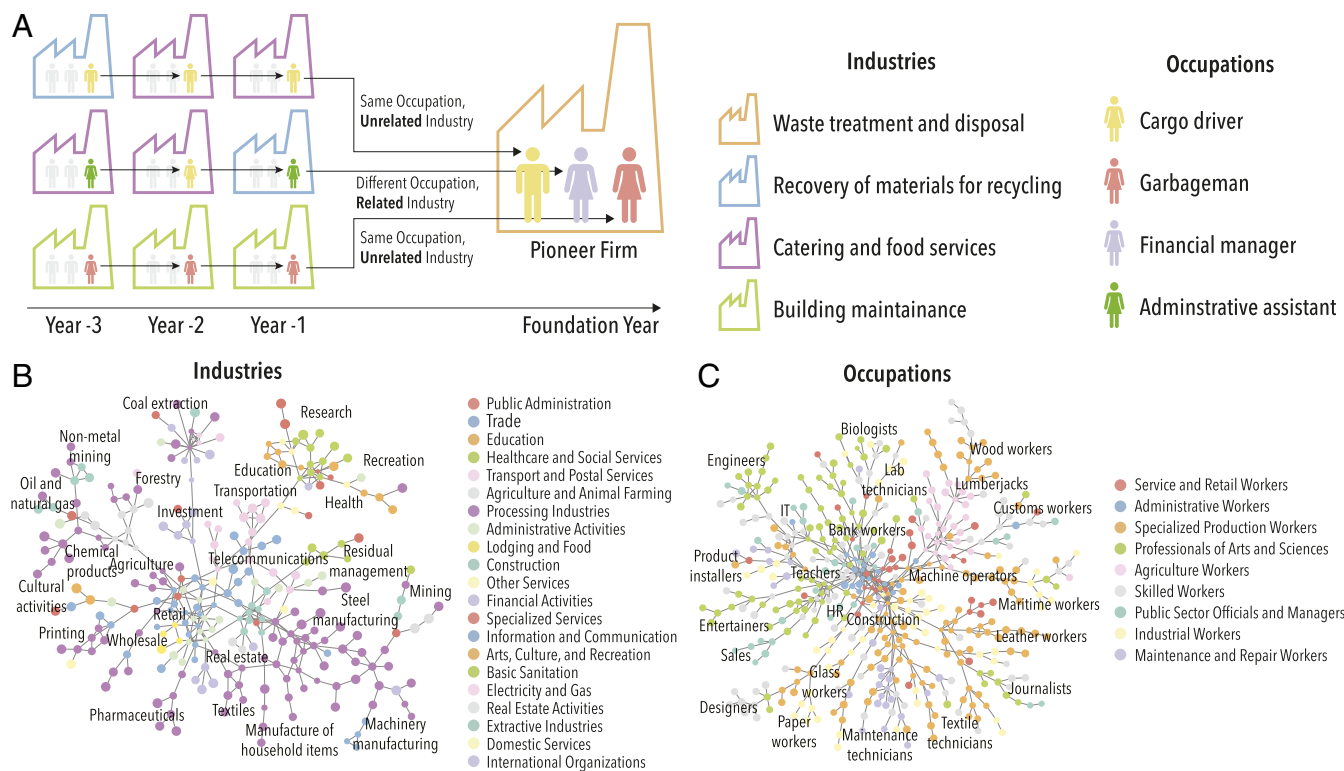


Fig. 2. Work histories and networks of related activities. The diagram in A shows how individual work histories are used to infer the knowledge brought into the pioneer firm by its first hires. The color of each worker represents his or her occupation, while the color of the bounding box represents the industry. The yellow worker, for example, has experience as a cargo driver, the same occupation he was hired to perform in the pioneer firm, but comes from a very unrelated industry. The light blue worker has experience in a different occupation, but in a related industry. B shows the network of related industries and C shows the network of related occupations. In C, node colors correspond to the highest level of the classification for occupations and industries. Shown are only the most important edges in each network, selected based on a trimming algorithm that starts with the maximum spanning tree and then adds all edges above a threshold (see *SI Appendix* for details).

going from i to i' and from i' to i between years $t-1$ and t . $g_{ii'}^{(t)} = \max\{g_i^{(t)}, g_{i'}^{(t)}\}$ is the maximum growth rate in the number of employees $g_i^{(t)} = \ln L_i^{(t)} - \ln L_i^{(t-1)}$ between both industries, $\tilde{L}_{ii'}^{(t)} = \max\{L_i^{(t)}, L_{i'}^{(t)}\}$ is the maximum number of employees between both industries in log-scale, and $L_i^{(t)}$ is the number of employees of industry i in year t , also in log-scale. We normalize the residuals $\hat{\gamma}_{ii'}^{(t)}$ to keep them between zero and one (see Eq. 2). We measure relatedness between occupations o and o' in an analogous way (Eqs. 3 and 4):

$$F_{i \leftrightarrow i'}^{(t)} = \beta_0 + \beta_1 g_{ii'}^{(t)} + \beta_2 \tilde{L}_{ii'}^{(t)} + \gamma_{ii'}^{(t)}, \quad [1]$$

$$\phi_{ii'}^{(t)} = \begin{cases} \frac{\hat{\gamma}_{ii'}^{(t)} - \min_{ii'}\{\hat{\gamma}_{ii'}^{(t)}\}}{\max_{ii'}\{\hat{\gamma}_{ii'}^{(t)}\} - \min_{ii'}\{\hat{\gamma}_{ii'}^{(t)}\}}, & i \neq i' \\ 1, & i = i' \end{cases} \quad [2]$$

$$F_{o \leftrightarrow o'}^{(t)} = \beta_0 + \beta_1 g_{oo'}^{(t)} + \beta_2 \tilde{L}_{oo'}^{(t)} + \theta_{oo'}^{(t)}, \quad [3]$$

$$\psi_{oo'}^{(t)} = \begin{cases} \frac{\hat{\theta}_{oo'}^{(t)} - \min_{oo'}\{\hat{\theta}_{oo'}^{(t)}\}}{\max_{oo'}\{\hat{\theta}_{oo'}^{(t)}\} - \min_{oo'}\{\hat{\theta}_{oo'}^{(t)}\}}, & o \neq o' \\ 1, & o = o' \end{cases} \quad [4]$$

Relatedness among industries and among occupations defines two weighted undirected networks for each year. Fig. 2 B and C shows the networks of related industries and occupations for 2008, after selecting the most important edges for the purpose of visualization (see *SI Appendix* for details). All of our analyses are conducted with the full, time-dependent, weighted networks.

Next, we use these measures of relatedness to create indicators of the stock of related knowledge that workers bring into pioneer firms. For each pioneer firm, we measure the amount of industry- and occupation-specific knowledge brought into it by its workers by aggregating relatedness across all its workers,

$$\Phi_{f,i,r}^{(t)} = \sum_{i'} s_{f,i',r} \phi_{ii'}^{(t)} \quad [5]$$

$$\Psi_{f,i,r}^{(t)} = \sum_{o'} s_{f,o,o'} \psi_{oo'}^{(t)}, \quad [6]$$

where $s_{f,i'}$ is the fraction of workers in firm f with experience in industry i' , and $s_{f,o,o'}$ is the fraction of workers in firm f performing occupation o with experience in occupation o' .

These two aggregate variables quantify, respectively, the industry- and occupation-specific knowledge that workers bring—based on their previous experience—into a pioneer firm f .

Fig. 3A shows a bivariate histogram of the number of pioneer firms starting with a certain stock of industry- and occupation-specific knowledge. We note that the median relatedness between a pair of industries or a pair of occupations is about 0.4, so most pioneer firms hire workers with a level of industry and occupation relatedness that is much higher than if they would be hiring those workers at random. The best interpretation of this fact is that the firms and workers recognize the importance of related knowledge and search and hire accordingly. When we study the histogram, we observe that pioneer firms tend to hire workers with occupation-specific knowledge (top rows in Fig. 3A) but only with an intermediate level of industry-specific knowledge (middle columns in Fig. 3B).

Next, we look at the pioneer firms that survive. Fig. 3B shows a bivariate histogram for the average 3-y survival rate of pioneer firms. Surprisingly, the distribution of surviving firms is quite different from the distribution of all pioneer firms. While pioneer firms tend to hire workers with occupation-specific knowledge, surviving pioneer firms tend to be those that hired workers with high levels of industry-specific knowledge (Fig. 3B). In fact, the 3-y survival rate of pioneer firms increases from about 60% when workers do not have industry-specific knowledge to more than 85% when workers bring an average industrial relatedness of more than $\Phi_f > 0.5$ (Fig. 3E). Fig. 3D shows the growth in employment of surviving pioneer firms. Here we see that pioneer firms with high stocks of industry-specific knowledge also

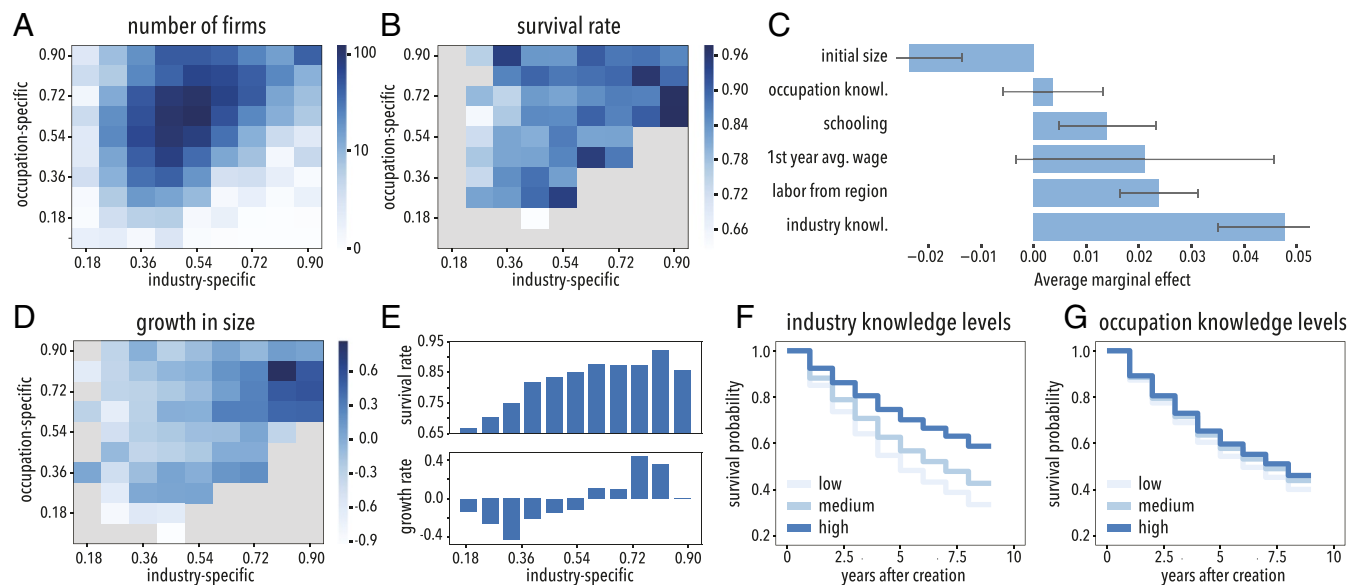


Fig. 3. Characteristics of pioneer firms that started after 2008, as a function of the industry- and occupation-specific knowledge (knowl.) brought by their workers. (A) The number of firms observed in the data. (B) The empirical survival rate at the third year. (D) The empirical employment growth rate at the third year of firms that survived. (E) Survival rate and growth rate as a function of industry-specific knowledge only. The gray color represents situations with not enough data points. (C) The average marginal effect on survival of each variable for model 6 from Table 1, for firms that started after 2008. (F) The predicted values for model 5 from Table 3 for firms that started in 2005, for different levels of industry-specific knowledge: low, medium, and high. (G) Similar to F, but for different levels of occupation-specific knowledge. In both F and G, low means the smallest observed value among pioneers, medium means the median of the observed values, and high means the maximum observed value.

grow much faster than those lacking industry-specific knowledge (Fig. 3E).

We formalize these results using multivariate regression analysis that predicts the 3-y survival rate $S_{f,i,r}^{(t+3)}$ and employment growth $G_{f,i,r}^{(t+3)}$ of pioneer firm f , operating in industry i and region r . We use logistic regression to predict the 3-y survival rate and ordinary least squares (OLS) to predict growth. We focus on the 3-y survival rate as a simple way to address right censoring of our data (companies that outlive our observation period). If we were to study survival at longer time periods using a logistic model, we would have to shrink the pool of pioneer firms we can track (for alternative models see *SI Appendix*).

Our models for survival and growth are a function of the firm's stock of industry-specific knowledge (Φ), occupation-specific knowledge (Ψ), average years of schooling of its workers (edu), number of initial workers (n_0), average wage (w), and local knowledge (ρ), which we define as the fraction of workers with work experience in the same region. In all of our models, the four knowledge variables (Φ, Ψ, edu, ρ) are measured in units of SDs from their respective means, to make their coefficients more easily interpretable and comparable. Formally, our models take the form defined in Eqs. 7 and 8. The model in Eq. 7 is a logistic regression, and $\mu_i, \lambda^{(t)}$, and η_r from Eqs. 7 and 8 are industry, year, and region fixed effects, respectively. Because we control for these fixed effects, our model can capture the effect of different types of human capital on firms' survival and growth, while controlling for time-invariant characteristics of industries and regions (such as the life cycle of an industry), as well as nationwide trends. Moreover, by adding the initial number of workers and the average wage of each firm, we are controlling for size effects and for the other effects regarding how attractive the jobs at each firm are.

Table 1 presents the results for both models for pioneer firms, with Φ, Ψ, edu , and ρ measured in SD units. Across all specifications the effects of industry-specific knowledge (Φ) in the survival and growth of firms remain strong, whereas the effects of

occupation-specific knowledge (Ψ) and schooling (edu) are weak when considered in isolation and insignificant after controlling for industry-specific knowledge (Φ). Fig. 3C shows the average marginal effects for model 6 from Table 1. An increase in 1 unit of SD of industry-specific knowledge leads to an average $\sim 5\%$ increase in the firm's probability of survival:

$$S_{f,i,r}^{(t+3)} = \beta_0 + \beta_1 \Phi_{f,i,r}^{(t)} + \beta_2 \Psi_{f,i,r}^{(t)} + \beta_3 edu_{f,i,r}^{(t)} + \beta_4 \rho_{f,i,r}^{(t)} + \beta_5 \log(n_{0,f,i,r}^{(t)}) + \beta_6 \log(w_{f,i,r}^{(t)}) + \mu_i + \lambda^{(t)} + \eta_r + \varepsilon_{f,i,r}^{(t)} \quad [7]$$

$$G_{f,i,r}^{(t+3)} = \beta_0 + \beta_1 \Phi_{f,i,r}^{(t)} + \beta_2 \Psi_{f,i,r}^{(t)} + \beta_3 edu_{f,i,r}^{(t)} + \beta_4 \rho_{f,i,r}^{(t)} + \beta_5 \log(n_{0,f,i,r}^{(t)}) + \beta_6 \log(w_{f,i,r}^{(t)}) + \mu_i + \lambda^{(t)} + \eta_r + \varepsilon_{f,i,r}^{(t)} \quad [8]$$

Is industry-specific knowledge important only for pioneer firms or for all new firms? Table 2 shows a comparison between pioneers and other nonpioneer new firms. The industry knowledge coefficient for nonpioneers is significantly lower than for pioneers (the interaction term in model 3 is positive and significant), and for nonpioneers the occupation knowledge coefficient remains significant even when we consider it together with industry-specific knowledge. Although we cannot reject the view that general knowledge and occupation-specific knowledge matter both for pioneers and for all firms, our results show that their effect is small compared with industry-specific knowledge. In fact, the point estimate for schooling is actually larger for pioneers than for all new firms. These results suggest that industry-specific knowledge is more important for pioneer firms than for new firms.

To explore the long-run impact of knowledge on survival, we focus on firms that started operating in 2005 and use the Cox proportional ratios model (24, 25) with a similar specification to that before (Eq. 7). Since we are using only pioneers from

Table 1. Estimates of the effect of different types of knowledge on the survival rate (models 1–6, logistic regressions) and growth rate (models 7–12, OLS) at the third year for pioneer firms

Independent variables	Dependent variable											
	Survival rate at third year, $S^{(t+3)}$						3-y growth rate, $G^{(t+3)}$					
	1	2	3	4	5	6	7	8	9	10	11	12
Industry knowledge (Φ)		0.466*** (0.114)				0.457*** (0.123)		0.174*** (0.029)				0.185*** (0.031)
Occupation knowledge (Ψ)			0.184** (0.085)			0.035 (0.092)			0.033 (0.022)			-0.029 (0.023)
Years of schooling (edu)				0.163* (0.086)		0.134 (0.091)				0.023 (0.025)		0.012 (0.025)
Local knowledge (ρ)					0.238*** (0.071)	0.228*** (0.072)					0.014 (0.019)	0.007 (0.019)
Initial size ($\log(n_0)$)	-0.246*** (0.093)	-0.251*** (0.095)	-0.261*** (0.094)	-0.226** (0.092)	-0.235** (0.093)	-0.227** (0.096)	-0.393*** (0.031)	-0.394*** (0.030)	-0.395*** (0.031)	-0.391*** (0.031)	-0.393*** (0.031)	-0.391*** (0.030)
Average wage ($\log(w)$)	0.208 (0.220)	0.136 (0.233)	0.188 (0.221)	0.137 (0.224)	0.342 (0.235)	0.202 (0.257)	0.231*** (0.071)	0.209*** (0.069)	0.228*** (0.071)	0.221*** (0.072)	0.238*** (0.072)	0.208*** (0.071)
Year f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,632	1,632	1,632	1,632	1,632	1,632	1,376	1,376	1,376	1,376	1,376	1,376
McFadden	0.2128	0.2265	0.2161	0.2153	0.2212	0.2367						
AICc	1,635.9	1,619.1	1,633.9	1,635.0	1,626.6	1,612.7						
Log-likelihood	-558.1	-548.4	-555.8	-556.3	-552.1	-541.1						
R^2							0.324	0.343	0.325	0.324	0.324	0.344
Adjusted R^2							0.194	0.216	0.194	0.194	0.194	0.215
F statistic							2.490*** (df = 222)	2.699*** (df = 223)	2.487*** (df = 223)	2.481*** (df = 223)	2.480*** (df = 223)	2.665*** (df = 226)

For all models reported SEs are robust and clustered by region, and the four knowledge variables are expressed in SD units. * $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$. SEs are in parentheses. df, degrees of freedom; f.e., fixed effects.

Table 2. Survival and growth at the third year for pioneer firms (models 1 and 4), nonpioneer firms (models 2 and 5), and all new firms (models 3 and 6)

Independent variables	Dependent variable					
	Survival rate at third year, $S^{(t+3)}$			3-y growth rate, $G^{(t+3)}$		
	1	2	3	4	5	6
Industry knowledge (Φ)	0.457*** (0.123)	0.091*** (0.007)	0.091*** (0.007)	0.185*** (0.031)	0.054*** (0.002)	0.054*** (0.002)
Pioneer dummy			0.156 (0.126)			0.088** (0.038)
Industry knowledge: pioneer dummy			0.203** (0.093)			0.091*** (0.027)
Occupation knowledge (Ψ)	0.035 (0.092)	0.035*** (0.007)	0.036*** (0.007)	-0.029 (0.023)	0.012*** (0.002)	0.011*** (0.002)
Years of schooling (edu)	0.134 (0.091)	0.008 (0.007)	0.009 (0.007)	0.012 (0.025)	0.002 (0.002)	0.002 (0.002)
Local knowledge (ρ)	0.228*** (0.072)	0.084*** (0.006)	0.085*** (0.006)	0.007 (0.019)	-0.007*** (0.002)	-0.007*** (0.002)
Firm controls	✓	✓	✓	✓	✓	✓
Year f.e.	✓	✓	✓	✓	✓	✓
Industry f.e.	✓	✓	✓	✓	✓	✓
Region f.e.	✓	✓	✓	✓	✓	✓
Firm type	Pioneers	Nonpioneers	All	Pioneers	Nonpioneers	All
Observations	1,632	284,369	286,001	1,376	242,192	243,568
McFadden	0.2367	0.0404	0.0404			
AICc	1,613	231,739	233,106			
Log-likelihood	-541	-115,638	-116,320			
R^2				0.344	0.152	0.152
Adjusted R^2				0.215	0.151	0.151
F statistic				2.665*** (df = 226)	188.475*** (df = 230)	188.274*** (df = 232)

The interaction between industry knowledge and a dummy for pioneers is positive and significant, meaning that the effect of industry-specific knowledge is larger for pioneer companies. As before, all knowledge variables are expressed in SD units. Firm controls include initial size and average wage. * $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$. SEs are in parentheses. AICc, corrected Akaike Information Criterion; df, degrees of freedom; f.e., fixed effects.

1 y, a fixed-effects model would lead to model overspecification. Instead, we control for region and firm characteristics as shown in Table 3. Fig. 3F and G shows the predicted values for the survival rate of pioneer firms according to model 5 from Table 3, for firms with low, medium, and high levels of industry-specific knowledge (Fig. 3F) and occupation-specific knowledge (Fig. 3G). Industry-specific knowledge has more distinctive effects on the survival rate than occupation-specific knowledge (more details in *SI Appendix*).

The endogeneity of firm entry and hiring decisions both challenge these results. Perhaps, more productive firms just tend to hire related industry workers. Perhaps occupation-specific knowledge does not matter, because firms enter only when they anticipate their ability to make up for any lack in occupation-specific skill. We cannot address all endogeneity concerns, but we use shocks to the supply of related human capital at the local level as an instrument of hiring such workers.

Here, we construct a Bartik labor supply shock B_{ri} (19, 26, 27), using the demand shocks experienced by other related industries. In other words, we use the growth or decline of industry i' at the national level, as a supply shock that respectively decreases or increases the availability of the workers with industry-specific knowledge required by industries related to i' . For instance, if the manufacturing of cars and motorcycles is related in terms of industry-specific knowledge, a demand boom in the car sector would cause a shortage of workers with knowledge relevant to the manufacturing of motorcycles in the regions where the car industries are growing. Consequently, we should expect a pioneer firm in the motorcycle industry to hire fewer

workers with industry-specific knowledge when the industries related to motorcycle manufacturing are experiencing national-level booms. This means the expected correlation, through this mechanism, between the Bartik instrument B_{ri} and the number of workers with industry-specific knowledge hired by a pioneer firm Φ_f should be negative.

We define the industry-specific knowledge Bartik shock on industry i in region r as

$$B_{ri}^{(ind)}(t) = \sum_{i', i' \neq i} g_{i',r}^{(t)} \frac{\phi_{ii'}^{(t)} L_{ri'}^{(t)}}{\sum_{i', i' \neq i} \phi_{ii'}^{(t)} L_{ri'}^{(t)}}, \quad [9]$$

where $\phi_{ii'}^{(t)}$ is the relatedness between industries i and i' , using flows between $t-1$ and t , $g_{i',r}^{(t)} = \log(L_{i',r}^{(t)}) - \log(L_{i',r}^{(t-1)})$ is the employment growth of industry i in every region except in region r , and $L_{i',r}^{(t)}$ is the number of workers in year t in industry i removing region r . $L_{ri'}^{(t)}$ is the number of people working in industry i' in region r . Eq. 9 has the same form as the original Bartik shock, since it is an interaction between the national trend ($g_{i',r}^{(t)}$) and the local industrial structure ($L_{ri'}^{(t)}$), but weighted by the similarity with industry i ($\phi_{ii'}^{(t)}$).

Table 4 shows the results of using $B_{ri}^{(ind)}$ as an instrument for industry knowledge Φ to estimate the effect of industry-specific knowledge in the growth of pioneer firms. Our two-stage least-squares estimates confirm the sign of the effect found using OLS.

Table 3. Cox proportional hazards model for pioneer firms that started in 2005

Independent variables	Dependent variable: Death probability				
	1	2	3	4	5
Industry knowledge (Φ)	-0.214** (0.089)				-0.181** (0.092)
Occupation knowledge (Ψ)		-0.107* (0.059)			-0.038 (0.063)
Years of schooling (<i>edu</i>)			-0.129** (0.057)		-0.105* (0.058)
Local knowledge (ρ)				-0.145*** (0.047)	-0.144*** (0.048)
Region controls	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓
Observations	462	462	462	462	462
R ²	0.026	0.019	0.023	0.032	0.054
Wald test	11.580 (df = 8)	9.070 (df = 8)	10.790 (df = 8)	15.660** (df = 8)	25.840*** (df = 11)

Firm controls include initial size and average wage, and region controls include population, GDP per capita, average schooling, available industry-specific knowledge, and the survival rate of nonpioneer firms as a control for how competitive the region is. As before, all knowledge variables are expressed in SD units. * $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$. df, degrees of freedom.

Discussion

Here we use the entire work history of Brazil to create measures for the knowledge carried by workers into new activities and study how these different types of knowledge affect the growth and survival of pioneer firms. Pioneer firms—new firms operating in an industry that is new for the region—are of particular interest because their success represents an increase in regional economic diversification. Our work shows that industry-specific knowledge is particularly important, since pioneer firms that hire workers with experience in a related industry grow faster and are more likely to survive. Surprisingly, the effects of occupation-specific knowledge and general schooling are not significant for pioneer firms, while being important for newly formed nonpioneer firms.

Knowledge diffusion is acknowledged to be a key driver of economic development. In fact, countries and cities have been shown to be more likely to develop new economic activities that are similar to their existing activities (11, 13, 14, 29, 30). This effect has proved so strong that, at the international level, less than 8% of the recorded diversification events between 1970 and 2010 were into unrelated products (31). However, most research on industrial diversification has focused on macrolevel dynamics. Here we contribute to this body of literature by studying the microlevel mechanisms that might lead to these types of observations (32).

The idea that workers carry the knowledge that economies need to grow and diversify is not new. However, knowledge and human capital are usually conceptualized as measures of intensity (years of schooling for example). Our evidence suggests that knowledge is better understood in terms of relatedness since workers differ not only in their total knowledge, but also in what this knowledge is about. Here we have shown that general knowledge, measured as average years of schooling, is not a strong determinant of the survival of a pioneer firm, but that the relatedness of knowledge between past and present activities is.

Moreover, we show that for pioneer firms, industry-specific knowledge is a stronger predictor of survival and growth than occupation-specific knowledge. This is an unexpected finding.

One explanation for this might be that the first hires of a pioneer company often end up taking some managerial role, while not operating directly as managers. For these roles, industry-specific knowledge might be more important than occupation-specific knowledge. Another possible explanation could be simply that industry-specific skills take longer to acquire than occupation-specific skills, and hence, firms with more in-house industry experience have an advantage at the outset.

Imagine the case of a salesperson. Salespeople are essential for the growth and survival of firms and have both occupation- and industry-specific knowledge. The occupation-specific knowledge of a salesperson involves knowledge on how to communicate with clients, develop relationships, and close deals. These are skills that can be easily transferred from one firm to the next. The industry-specific knowledge required by a salesperson, however, depends strongly on the product or service being sold. A salesperson with experience in selling garments may struggle selling enterprise software, not because she cannot develop a relationship with a client, but because she may lack the knowledge needed to understand the software needs of clients and the engineering capacity of her team. Lacking the experience needed to understand and communicate needs precisely, a salesperson without industry-specific knowledge can generate misunderstandings between clients and production teams that could be disastrous for a pioneer company.

Previous work has shown that the founder's experience is a strong predictor of the performance of startups (33). We do not know who the founder of the company is in our data, but we can check whether the observed effect is due to just one employee or whether it is a characteristic of the team. We find that an important part of the effect is driven by the most experienced (related) employee, but that there is a significant part that is due to the rest of the team. Even after we remove the most experienced member of the team from the sample and add her as a pioneer-specific control, our finding that industry-specific knowledge matters remains strong. This suggests that the most experienced employee is not driving all of the observed effect (*SI Appendix*).

Table 4. Results of using the Bartik shock defined in Eq. 9 as an instrument for the industry-specific knowledge brought to a pioneer firm by its first hires (Φ)

Independent variables	Dependent variable			
	Industry knowledge	3-y growth rate		
		First stage: 1	Reduced form: 2	Instrumental variable: 3
Industry knowledge ($\Phi^{(t)}$)			0.502** (0.256)	0.177*** (0.032)
Bartik shock ($B_{ri}^{(ind)}$)	-6.899*** (1.568)	-3.465** (1.686)		
Growth of industry ($g_{i,t}$)	0.282** (0.134)	-0.003 (0.144)	-0.144 (0.162)	0.056 (0.161)
Constant	-0.634*** (0.075)	0.496*** (0.081)	0.814*** (0.243)	1.898*** (0.549)
Observations	1,380	1,380	1,380	1,380
R ²	0.016	0.003		0.234
Adjusted R ²	0.015	0.002		0.089
F statistic	11.236*** (df = 2)	2.129 (df = 2)		1.609*** (df = 220)

Our two-stage least-squares estimates confirm the direction of the effect on growth found using OLS. The *F* test for the strength of the instrument yields a statistic of 18.339*** (28). Industry knowledge is expressed in SD units. * $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$. df, degrees of freedom.

Another explanation for our results is that workers from related industries are more likely to have connections to clients, customers, and trustworthy workers, so what they bring is not just their knowledge about the industry, but also their knowledge of the social network in which the industry is embedded (34, 35). This form of industry-specific social capital can be regarded as a subtype of industry-specific knowledge or experience and also should be reflected in the location-specific knowledge of a worker, which we find is a significant predictor of the growth and survival of pioneer firms. Unfortunately, there are few data sources that can be used to isolate the effects of skills and location with the pure effects of social capital, so the effects of embeddedness are hard to identify.

These findings add to the literature studying differences between industry- and occupation-specific knowledge in other contexts (36, 37). The industry-specific knowledge brought by a firm's manager, for example, has been shown to be very important for the productivity of the firm (22, 38). In fact, a manager's human capital has been shown to be mainly industry specific (39), in the sense that industry tenure provides a higher wage premium than occupational tenure. For other occupations such as craftsmen, human capital has been shown to be primarily occupation specific. Together with this body of literature, our study suggests that the picture where a job (an occupation for a given industry) is linked to a set of skills only through the occupation might be incomplete.

There is growing evidence of the effects of movement of industry-specific human capital on the development of regions. History shows that the migration of skilled workers encourages regional development of new industries. For example, in the 16th century, the region around Antwerp, Belgium was an industrial center for the textile industry, until the anti-

Protestant persecution in the late 16th century triggered an exodus of Protestant workers. Many of those skilled workers moved to the northern part of The Netherlands and helped develop new textile industries in those cities (40, 41). Similarly, other studies using pioneer plants have revealed the importance of industry-specific human capital (1), but have not compared it with general knowledge or occupation-specific knowledge.

Although our data are specific to Brazil, the great variation in income and industrialization level among Brazilian microregions suggests that our results might generalize. In fact, the richest Brazilian microregion had an average income per capita in 2013 of about USD \$28,000, which was comparable to that of Spain, Italy, or South Korea; while the poorest microregions had an average income of about USD \$5,000, which is comparable to that of Paraguay, Jamaica, or Algeria. Moreover, the vast geographic variation of wealth in Brazil makes it an interesting scenario for studying industrial development, since it combines the challenges of middle-income countries with the data-reporting quality of high-income countries. Finally, our results emphasize that to fully understand the importance of tacit knowledge for regional industrial diversification, it is important to measure knowledge along different dimensions. The work history of individuals may be the key to measuring these different types of knowledge.

ACKNOWLEDGMENTS. We thank Kerstin Enflo, Jian Gao, Tarik Roukny, and Siqi Zheng for comments, as well as Manuel Aristarán and Elton Freitas for data assistance. C.J.-F., B.J., and C.A.H. acknowledge support from the Massachusetts Institute of Technology (MIT) Media Laboratory Consortium; the MIT Skoltech Program; the Masdar Institute of Science and Technology (Masdar Institute), Abu Dhabi and United States, Reference 02/MI/MIT/CP/11/07633/GEN/G/00; and the Center for Complex Engineering Systems at King Abdulaziz City for Science and Technology.

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