DISCUSSION PAPER SERIES

DP15920

ON IMMIGRATION AND NATIVE ENTREPRENEURSHIP

Harriet Orcutt Duleep, David A. Jaeger and Peter McHenry

LABOUR ECONOMICS

ISSN 0265-8003

ON IMMIGRATION AND NATIVE ENTREPRENEURSHIP

Harriet Orcutt Duleep, David A. Jaeger and Peter McHenry

Discussion Paper DP15920
Published 15 March 2021
Submitted 14 March 2021

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

ON IMMIGRATION AND NATIVE ENTREPRENEURSHIP

Abstract

We present a novel theory that immigrants facilitate innovation and entrepreneurship by being willing and able to invest in new skills. Immigrants whose human capital is not immediately transferable to the host country face lower opportunity costs of investing in new skills or methods and will be more flexible in their human capital investments than observationally equivalent natives. Areas with large numbers of immigrants may therefore lead to more entrepreneurship and innovation, even among natives. We provide empirical evidence from the United States that is consistent with the theory's predictions.

JEL Classification: J15, J24, J39, J61, L26

Keywords: Immigration, Innovation, entrepreneurship, Human Capital

Harriet Orcutt Duleep - hduleep@wm.edu
College of William and Mary

David A. Jaeger - david.jaeger@st-andrews.ac.uk
University of St Andrews and CEPR

Peter McHenry - pmchenry@wm.edu
College of William and Mary

Acknowledgements
We thank Robert Fairlie for facilitating our use of his entrepreneurship data. For helpful comments, we thank Barry Hirsch, Michael White, Deb Cobb-Clark, and participants at the 2016 Southern Economic Association meetings, the 8th IZA Annual Migration Meeting in 2011, the 2010 meeting of the European Association of Labour Economists, seminars at the University of Bochum and Columbia University, the 2008 meeting of the Population Association of America, and the 2005 Conference “Immigration: Trends, Consequences and Prospects for the United States,” organized by Barry Chiswick. Particular thanks to Mark Steinmeyer and the Smith Richardson Foundation, who have supported the empirical work.

1 Introduction

Immigration to the United States increased substantially after the Immigration and Nationality Act of 1965 substantially removed national-origin quotas that had favored European countries, and shifted the source-country composition predominantly towards Asian and Latin American countries that are less economically developed than the U.S. This sea change in the quantity and character of American immigration – like the waves of immigrants that arrived in the 19th and 20th centuries – has led to concerns about the impact of the new immigrants on the U.S. economy. A subject of intense debate among academics and policy makers is to what extent this large flow of foreigners has had a negative or positive impact on natives' labor market outcomes and the overall growth of the economy.

Other than two important and provocative studies of patent activity (Chellaraj et al., 2008; Hunt and Gauthier-Loiselle, 2010), one aspect of immigrants' impact in the U.S. that has received scant attention is the degree to which immigration affects innovation and entrepreneurial activity. Although it is well known that certain groups of immigrants are more likely to be self-employed than U.S. natives, little is known about how immigrants affect business development, the general ability of firms (including those owned and run by natives) to innovate.[1]

We postulate that immigration encourages new business formation by providing a flexible labor supply that is both willing and able to invest in new skills. This thesis departs from other explorations of entrepreneurship and immigration that focus on immigrants as entrepreneurs, often starting small family businesses. Following Duleep and Regets (1999, 2002), we describe a theory of human capital investment decisions that focuses on the distinction between immigrants' human capital from their origins and human capital that they acquire in their destination country. Origin-country human capital is likely not to transfer

[1]Another area that has received very little attention is whether and to what degree immigrant entrepreneurs may displace native-born entrepreneurs. See Fairlie and Meyer (2003) for an analysis of this issue. Our study looks at the potential effect of immigrants on natives' entrepreneurship via a labor supply channel.

completely to labor market activities in the destination. Lower transferability reduces wages and thereby the opportunity cost of human capital investment in the destination country. In addition, human capital from the origin country (including the ability to learn) is likely to increase the productivity of human capital investments in the destination.

We argue that entrepreneurs and other innovators are likely to value immigrants' propensity to invest in new human capital in their destinations. Some new products and services are likely to require new skills and workers for whom skill acquisition is less expensive should prove valuable to firms. We therefore expect the presence of immigrants to foster entrepreneurship. The results in Hunt and Gauthier-Loiselle (2010) support our theory. In particular, they find that there is an immigrant effect on innovation beyond what can be explained by immigrants' own propensity to innovate, as measured by patent activity. Moreover, they find that the immigrant effect on the spill-over effect is greatest for highly educated immigrants – a finding also predicted by the immigration-innovation framework described in more detail below.

We test predictions of the immigrant human capital investment model with data from the Current Population Survey, the Kauffman Index of Entrepreneurial Activity, and the Census Bureau's Business Dynamics Statistics data base. We find that a higher share of immigrants in a state is associated with more subsequent entrepreneurship among natives in the state and job creation at the youngest firms. These relationships are clearest for college-educated immigrants from less-developed countries, consistent with the theory.

2 Theoretical Background

2.1 Immigrants, Natives, and Human Capital Investment

Chiswick (1978, 1979) theorized that migrants often lack skills specific to their destination country that would permit their home-country human capital to be fully valued in the host-country labor market. Immigrants initially earn less than similarly qualified U.S. natives because the specific skills and knowledge associated with their years of schooling and experience are not valued as much by U.S. employers as are the skills of individuals raised and schooled within the United States. To increase the U.S. labor market value of their home-country human capital, immigrants engage in many forms of human capital investment such as learning English, pursuing various forms of informal and formal U.S. school and training, and becoming knowledgeable about U.S.-specific institutions, production methods, and technical terms. The specific "skills" needed to increase the U.S. labor market value of home-country human capital may also include credentials, such as a diploma or training certificate that is recognized by U.S. employers or is needed to perform a particular kind of work in the United States. As English and other U.S.-specific skills or credentials are gained, the value of the immigrant's home-country human capital approaches that of a comparably educated and experienced U.S. native.

Building on Chiswick's work, Duleep and Regets (1999, 2002) introduced an immigrant human capital investment (IHCI) model that starts with Chiswick's concept of international skill transferability and highlights two implications. First, immigrants whose home-country skills do not fully transfer to the new labor market will, by virtue of their lower wages, have a lower opportunity cost of human-capital investment than natives. The time they spend learning new skills, instead of applying their current skills to earning, is less costly for them than it is for natives, who earn more with the same level of schooling and experience. Second, home-country skills that are not fully valued in the host-country labor market are nevertheless useful for learning new skills. Workers who have learned one set of skills – even if those skills are not valued in the destination-country labor market – have advantages in learning a new skill set. Those with home-country skills have learned how to learn. Moreover, common elements between old and new skills aid learning.[2]

To clarify these points Duleep and Regets (1999, 2002) used a simple two-period model to describe the human capital investments of natives:

[2]For more discussion on this point, refer to Duleep and Regets (1999, 2002).

$$\max_{\theta} wH_1(1-\theta) + w(H_1 + \gamma f(H_1, \theta)) \tag{1}$$

where w is the market rate of return on a unit of human capital, H_1 is the initial stock of human capital, and θ is the proportion of available time devoted to investment in the first period.[3] The production function of human capital is denoted $\gamma f(H_1, \theta)$ where f is a positive function of H_1 and θ. The human capital productivity coefficient γ may vary across individuals. For U.S. natives, the opportunity cost of training can be denoted as $wH_1\theta$. The return to training can be expressed as $w\gamma f(H_1, \theta)$. The optimal investment decision, θ^*, maximizes total earnings over the two periods.

Duleep and Regets note that even in this simple framework, the human capital investment decision of immigrants is more complicated and requires the introduction of two skill transferability parameters. An immigrant's initial stock of human capital, H_1, was produced in their source country and may not be fully valued in their destination country. It is necessary to introduce a factor, τ_M, the proportion of source-country human capital that is initially valued in the labor market of the destination country. This skill transferability parameter could be referred to as "skill transferability to the labor market." It formalizes the discussion of international transferability of skills introduced by Chiswick (1978, 1979).

An immigrant's initial stock of human capital may also not fully transfer to the production of new, destination-country, human capital. To capture this feature, Duleep and Regets introduce a factor, τ_P, the proportion of source-country human capital that transfers to the production of new, destination-country human capital. The second skill transferability parameter could be referred to as "skill transferability to human capital production." For immigrants, the two-period model of human capital investment becomes:

[3] While the proportion of time devoted to investment is a convenient concept, θ could also be usefully thought of as the proportion of the U.S. market value of initial human capital that is foregone as a result of investment. This broader concept would include traditional forms of human capital investment such as apprenticeships or simply taking a job with lower initial pay, but greater opportunity for advancement.

$$\max_{\theta} w\tau_M H_1(1-\theta) + w(\tau_M H_1 + \gamma f(\tau_P H_1, \theta)) \tag{2}$$

When $\tau_M < 1$, the opportunity cost of investment for immigrants is lower than for natives with the same level of human capital in period 1. Yet, despite lower opportunity costs, there would not necessarily be a greater incentive for immigrants to invest in destination-country human capital than natives. If $\tau_M = \tau_P$, the lower opportunity cost of investment resulting from low skill transferability to the labor market will be offset by higher human capital production costs. Duleep and Regets argue, however, that when $\tau_M < 1$, it will generally be the case that the proportion of source-country human capital that transfers to the labor market will be less than the proportion of source-country human capital that transfers to the production of new human capital. It seems safe to assume that human capital that transfers to the labor market will also transfer to the learning of new skills. Thus τ_P is at least as large as τ_M. But human capital that does not transfer to the labor market is still useful for learning new skills. Thus, when $\tau_M < 1$, it is likely that $\tau_M < \tau_P$: when immigrants' human capital does not fully transfer to the host-country labor market, imported human capital will be more effective in learning than in earning.

A lower opportunity cost of human capital investment combined with the usefulness of undervalued human capital for creating new human capital creates a greater incentive for immigrants to invest in human capital than natives with similar levels of education and experience. Since human capital investment fuels earnings growth, the IHCI model predicts that immigrants will experience higher earnings growth than natives. Among immigrants, there will be an inverse relationship between entry earnings and earnings growth.[4] Immigrants whose skills do not initially fully transfer to the U.S. will have lower initial earnings but

[4]Chiswick (1978, 1979) first predicted the inverse relationship with supporting evidence that U.S. immigrants from non-English-speaking countries had lower initial earnings but higher earnings growth than immigrants from English-speaking countries. Other confirmatory evidence includes Lalonde and Topel (1991, 1997), Duleep and Regets (1997, 1999, 2002), Jasso and Rosenzweig (1995), DeSilva (1997), Schoeni (1997), Demombynes (2002), Aydemir and Skuterud (2005), Akresh (2007), Green and Worswick (2012), Lin (2013), Villarreal and Tamborini (2018), Duleep et al. (2018), and Duleep et al. (2021).

higher earnings growth than immigrants with similar levels of schooling and experience, but more transferable skills.

Consistent with the IHCI model, studies that follow cohorts from their initial years in the U.S. and do not impose a relationship between entry earnings and earnings growth or impose sample constraints find an inverse relationship between immigrant entry earnings and earnings growth, and higher earnings growth for recent immigrants than natives (Duleep and Regets, 1999, 2002; Duleep et al., 2021, e.g.). Recent immigrants also appear to have a higher propensity than natives to invest in human capital, as measured by school enrollment in Duleep and Regets (1992) and occupational changes in Green (1999).

In addition to predictions about human capital investments of immigrants relative to natives, the IHCI model suggests that immigrants' own backgrounds will influence their human capital investments. Source-country human capital that is not valued in the destination-country labor market is useful for gaining new skills. Because source-country human capital is not fully valued in the host-country's labor market, it does not increase the opportunity cost of time spent in human capital investment in the host country. So, immigrants with more education from their origin countries are expected to invest more in U.S. human capital acquisition.

Furthermore, immigrants from less-developed countries likely experience more difficulty transferring their human capital to the U.S. labor market than immigrants from more-developed countries. Hence, immigrants from less-developed countries may be more inclined to invest in additional U.S. human capital than immigrants with similar origin-specific human capital levels from more-developed countries. Consistent with these predicted relationships between immigrants' origin-country human capital and subsequent investment decisions, Duleep and Regets (2002) find that the earnings growth of the more educated versus the less educated is higher among immigrants coming from economically developing countries than it is for immigrants coming from economically developed countries.

Relative to other immigrants, refugees are likely to have fewer transferable skills, since their migration was prompted by political changes rather than specific economic opportunities. The IHCI model implies that refugees may therefore invest in host-country human capital at relatively high rates.

A potential benefit of immigrants – particularly highly educated immigrants – lacking immediately transferable skills is a high rate of human capital investment that is not tied to restoring specific home-country skills. When market demand shifts require new skills among workers, immigrants who initially lacked U.S.-specific skills will be more likely to pursue the new opportunities than will natives or immigrants with highly transferable skills. Recent immigrants may be better equipped than natives to respond to the changing skill needs of an economy (Green, 1999).

2.2 Immigrant Skill Transferability, the Propensity to Invest in Human Capital, and Entrepreneurship

Viewing the IHCI model from the employer's perspective suggests that a high propensity to invest in human capital, not tied to restoring the value of specific home-country skills by immigrants, may encourage entrepreneurship and innovation. To innovate is to introduce something new, such as a new method or product. In the U.S. market economy, entrepreneurship is a principal route through which innovations occur. But what facilitates entrepreneurship? In deciding whether to develop a new product or service, potential entrepreneurs examine the costs and returns of pursuing such an activity. Returns are affected by the potential demand for a new product or service. In addition to capital outlays, a crucial cost of any new venture, particularly an innovative one, is training the workforce that will create the new product or service. New businesses require people who are willing and able to acquire new human capital. The extent to which this is true may be a function of how innovative the new business is. Indeed, one measure of innovativeness might be the distance between the skills needed to produce a new product or service and the existing set of skills: the greater the difference, the greater the innovation.

The cost of training employees to produce a new product or service is affected by the wage entrepreneurs have to pay employees while they are being trained and the return in terms of the value of the new human capital produced through the training. The wage entrepreneurs have to pay employees while they are being trained is determined by the opportunity cost of potential employees. That is, what can they get elsewhere? The above theory implies that training costs are relatively low for immigrants, in particular for highly-educated immigrants (with a larger or more-proven capacity to learn new skills) and immigrants from less-developed countries (whose human capital is less transferable to the U.S.). In terms of the model, highly-educated immigrants (high H_1 or similarly high τ_P) encourage innovation to the extent that $\tau_P > \tau_M$: origin-country human capital is more effective in learning innovative processes than in immediate applications to the workforce.

Finally, the above theory implies that the more innovative a particular venture is, the lower the training costs of immigrants relative to U.S. natives. We see this by returning to the notion of skill transferability. We stated that an immigrant's initial stock of human capital might not fully transfer to the production of new, destination-country, human capital (i.e., the possibility that $\tau_P < 1$). Yet, it also seems likely that the more innovative a product or service is, the greater the distance between the current set of available skills in the U.S. native labor force and the skills that would be needed for a new firm or industry. The more innovative it is, the less native-born skills would transfer to the new industry. The more innovative it is, the less the distance would be between τ_P for immigrants versus the U.S. born. At the same time, the opportunity cost of training for natives would be unaffected. This implies that the more innovative the venture, the more helpful the availability of immigrant labor would be.

3 Empirical specification

From the above discussion several testable hypotheses emerge that inform the specification of our empirical model:

1. Immigrants whose skills do not fully transfer to the U.S. ($\tau_P < 1$) have human capital that is undervalued in the U.S. labor market and yet useful for learning new skills. This translates into a higher propensity to invest in human capital – including human capital that is not tied to reviving the value of the immigrant's specific source-country human capital – hence a lower cost of training than observationally equivalent U.S. natives. We would therefore expect to find a positive effect of immigration on entrepreneurship.

2. For many immigrant groups, entrepreneurial ventures are characterized by small businesses in which the hires are paid and unpaid family members (Bates, 1996, e.g.). Our model suggests that immigration affects entrepreneurship and innovation via a labor supply effect. We would thus expect to find our anticipated immigration effect on the entrepreneurship and innovation of U.S. natives. This consideration suggests that in addition to testing for the effect of immigration on entrepreneurship in general, our empirical specification should separately test for the effect of immigration on U.S. native-only entrepreneurship.

3. The propensity to invest in human capital by immigrants tends to increase with education (through a higher τ_P). Therefore, we would expect the immigration effect on entrepreneurship to be most consistently apparent for highly educated immigrants. Our empirical specification should permit examining the effect of immigration on entrepreneurship by immigrants' level of schooling. Moreover, we would like our empirical specification to allow a comparison of the respective effects of highly educated immigrants versus highly educated natives on entrepreneurship.

4. The model also implies that a lower transfer rate of human capital (τ_M) induces a greater post-immigration investment in human capital (since the opportunity cost is relatively low). We proxy for transferability with the level of development of immigrants' origin

countries and whether the country of origin is a significant source of refugees.[5] We expect that immigrants from less-developed countries and refugees should have a stronger effect on entrepreneurship than immigrants from more-developed countries.

5. Business startups typically experiment with a variety of new methods, products, and processes. We would thus expect that the effect of immigration on the creation of new establishments would be most relevant to the start-ups of new establishments by young firms versus new establishments in old firms. This suggests that our empirical specification should permit examining the effect of immigration on new establishment creation by the age of the firm.

To test those hypotheses, we estimate empirical specifications of the following form:

$$\text{Entrep}_{st} = \alpha_s + \beta_t + \gamma \text{Imm}_{s,t-1} + \delta \text{Unemp}_{st} + u_{st} \tag{3}$$

where s is state, and t is year. Entrep_{st} is a measure of entrepreneurship (or business dynamics) specific to state s in year t. $\text{Imm}_{s,t-1}$ is a measure of a lagged local immigrant stock (e.g., share of labor force that is immigrants). Unemp_{st} is the state-specific unemployment rate, and u_{st} is an error term. Specifications are weighted so that each observation's weight is the inverse of the standard error of the estimate for Entrep_{st}. Regression coefficient standard errors account for clustering at the state level.

In light of the theoretical analysis, we modified this basic empirical specification to include state and year-specific shares of immigrants and shares of natives by education level. In some specifications, we also distinguish between immigrants from less- and more-developed countries. Adding these shares to the model permits us to test how immigration's effect on entrepreneurial activity changes with immigrants' level and origin of schooling. This formulation also lets us measure the effect on business formation and entrepreneurial activity of immigrants, by schooling level, relative to natives with similar levels of schooling.

In addition to the above issues that flow from the theoretical conceptualization under-

[5]All refugee-contributing countries in our time span are also economically developing countries.

lying our model, there is a concern about causality: Does immigration affect entrepreneurship/innovation, or does entrepreneurship/innovation affect immigration? That is, if we find a positive relationship between state-level immigration and entrepreneurship, does it simply reflect a process wherein immigrants move to areas and industries that are entrepreneurial and innovative?

To control for omitted variables that could affect both immigration and entrepreneurship, we include time (β_t) and state (α_s) fixed effects as well as time and state-specific measures of unemployment (Unemp_{st}). State fixed effects condition on time-invariant differences across states in entrepreneurship. The unemployment rate controls for state-level business cycles that influence both business formation and immigrants' location decisions. The timing of our measurements of immigration and entrepreneurship also reinforces our interpretations. If immigrants sort into more entrepreneurial states – which would compromise our inference – then we might expect immigration to follow entrepreneurship. Instead, we investigate models with immigration measures that pre-date entrepreneurship (that is, immigration is measured at a lag).

In addition, we compare the relationships of both native and immigrant local labor supply with entrepreneurship. Both natives and immigrants may sort into more entrepreneurial states and thereby compromise our inference. Indeed, geographic mobility among the highly-educated is relatively responsive to local economic conditions (Wozniak, 2010). However, if immigrant labor supply has a stronger relationship with entrepreneurship than natives' supply, then the case for a human capital investment interpretation is strengthened. The reason is that both immigrants and natives should respond to local economic conditions. Cadena and Kovak (2016) study migration responses of native-born and foreign-born workers to local demand shocks. While their main finding is that Mexican-born low-skilled workers are particularly responsive, their instrumental variables results show that among the highly educated, immigrants are not more mobile than natives in response to local economic conditions (Tables 4 and 6).

4 Data

4.1 Kauffman Index of Entrepreneurial Activity

Data that measure business creation is key to the success of our endeavor. One approach would be to measure the creation of new businesses by differencing establishment counts over consecutive periods of time. A second measure of business formation would be to difference counts of the total number of individuals in non-farm self-employment from the Current Population Survey (CPS) and decennial Census data.

These measures are problematic because changes in the number of businesses or entrepreneurs reflect both new businesses and business deaths. For instance, in the state- and time-specific statistics, an increase in the number of firms or entrepreneurs could be due to increased business creation or to fewer firms and entrepreneurs going out of business or to some combination of these processes.[6]

We measure state-year entrepreneurial activity with the Kauffman Index of Entrepreneurial Activity. This series measures month-to-month transitions to self-employment. Pioneered by Robert Fairlie, new business ventures are counted by identifying new entrepreneurs. Linking monthly CPS files, one can follow individuals. New entrepreneurs are identified by finding in the first file of any year respondents who do not own a business as their main job (defined as 15 or more hours worked in general per week) and then determining whether these individuals own a business as their main job in the following survey month. CPS data identifying these month-to-month transitions to self-employment as well as other individual-level variables including immigrant status are available on the Kauffman Foundation website.

We downloaded the raw files used to calculate the KIEA annually from 1996 to 2013. We use the version of the entrepreneurship variable that ignores allocated values. We calculate for each state and year the share of new entrepreneurs as the weighted average of the en-

[6] We needed data on the initiation of new firms and the initiation of entrepreneurial activities. This requires data with either the age of the firm or some other indication of the initiation of a new business enterprise.

trepreneurship indicator variable, where weights are the Census person weights. We calculate separate entrepreneurship measures for the entire sample, for the native-born population, and for immigrants.

4.2 Business Dynamics Statistics

Our second set of outcome variables measure state-year changes in the creation of businesses and jobs. The Census Bureau maintains a business register with annual historical data; its records include when each establishment started. The Longitudinal Business Database links together the files from the Business Register and other relevant data (e.g., the economic census) to form longitudinal data on establishments. The Longitudinal Business Database contains the start date of any given establishment and other characteristics including location (state).

The Census Bureau makes available a public-use version of information from the Longitudinal Business Database and calls it the Business Dynamics Statistics (BDS). The BDS data set describes creation and destruction of jobs, establishments, and firms in the U.S. We use the state and year version of the data set to calculate various rates that describe business dynamics. In particular, we calculate the job creation and establishment entry rate for each state and year. We also calculate a set of variables that describe dynamics specific to the youngest firms in the state (less than one year old): the job creation rate among the youngest firms, the share of all job creation accounted for by the youngest firms, the share of total employment at the youngest firms, and the establishment entry rate among the youngest firms.

4.3 Current Population Survey

We use annual Current Population Survey (CPS) data to measure state-level immigrant and native labor force shares by education level and also unemployment rates (Flood et al., 2015). Our CPS data cover the period 1994 to 2013. We select the sample to include those between 20 and 64 years old (inclusive), not in the armed services, and not self-employed. We define immigrants as respondents who were foreign-born and either naturalized citizens or not citizens. We define education categories as high (bachelor's degree or greater), medium (high school diploma or equivalent, or some college less than bachelor's degree), and low (up to twelve years with no high school diploma). We use CPS weights to aggregate subgroup populations and then calculate the ratio of group population to total population. In that way, we measure immigration stock variables as weighted shares of populations. For example, the high-skilled immigrant share regressor is the estimated (with weights) count of immigrants with a bachelor's degree or more education in a state's labor force divided by the overall count (estimated with weights) in that state's labor force. Other education levels and native shares are measured correspondingly. In some alternative specifications, we measure population shares rather than labor force shares.

We also categorize immigrants' origins (countries of birth) as either more-developed or less-developed based on country Gross Domestic Product (GDP) per capita in 1990 using data from the World Bank (World Bank, 2016) and the International Monetary Fund (International Monetary Fund, 2015). When data from the World Bank were missing, we replaced them with values from the IMF. For some respondents, the CPS records give region rather than country of origin, and in those cases, we calculated a population-weighted average of country-specific GDP per capita values for each region. We rank countries and call them "more-developed" if their 1990 GDP per capita was greater than 11,200. "More-developed" origin countries are those in Western Europe excluding Portugal and Greece, plus Canada, Japan, Hong Kong, Singapore, Australia, New Zealand, U.S. Virgin Islands, Bahamas, Bermuda, UAE, and Israel; all other countries are "less-developed."

Unemployment rates are calculated using the CPS at the state-year level and used as a control variable. We calculate the weighted sum of unemployed respondents and the weighted sum of respondents in the labor force in each state-year. The ratio of these is the unemployment rate.

5 Results

5.1 Immigrants and KIEA entrepreneurship

Summary statistics for the entrepreneurship data from the KIEA and our CPS samples are in Table 1. The first panel shows that entrepreneurship is not very common but is more common among immigrants than the native-born. The average of state-year overall immigrant labor force shares is almost 10 percent. Almost half of these are in the medium-skill category, and the rest are distributed evenly between high-skilled and low-skilled. Immigrants from less-developed countries are more abundant than immigrants from more-developed countries. Low-skilled immigrants from more-developed countries are quite rare, but there are larger average shares of immigrants in other origin and skill categories.

We present our first tests of model predictions about the relationship between immigrants in the labor force and subsequent entrepreneurship in Table 2. The dependent variable in the five columns of the first panel is the entrepreneurship rate among all workers in the state-year. The first column implies that the relationship between overall immigrant shares and subsequent overall entrepreneurship is essentially flat. Columns 2, 4, and 5, however, display a positive relationship between high-skilled (college-educated) immigrants and entrepreneurship. Specifications that control for high-skilled natives in the state do not show a relationship between natives and entrepreneurship, which might be present if high-skilled workers sorted into increasingly entrepreneurial states over time. These results are consistent with the IHCI model's prediction that high-skilled immigrants are associated with increased entrepreneurship, perhaps indicating an increased productivity of investments and innovation. The column 5 specification shows that the relationship is only present for high-skilled immigrant shares, not lower-skilled shares. The bottom panel of Table 2 shows analogous results that substitute the entrepreneurship of the native-born for the overall rate. Results here are similar to the top panel: high-skilled immigrants are associated with elevated entrepreneurship. Since the entrepreneurship measure is specific to the native-born, these specifications should not be identifying merely the greater likelihood of immigrants themselves to start new businesses.

In Table 3 we show similar results but distinguish between immigrants from more-developed and less-developed origins. The IHCI model leads to the expectation that entrepreneurship should be more closely related to immigrants from less-developed countries, since their human capital probably transfers to the U.S. at a lower rate, thereby reducing their opportunity costs of human capital investment. Consistent with the model's prediction, in columns 3 and 4 of Table 3 the relationship between immigrants and entrepreneurship is indeed clearer when focusing on high-skilled immigrants from less-developed countries (although the difference in point estimate magnitudes between more- and less-developed origins is not large and is estimated imprecisely). The same is true in the bottom panel where the dependent variable is entrepreneurship among the native-born only.

We next consider specifications where the dependent variable is entrepreneurship among immigrants in the state. Regressions in Table 4 show that high-skilled immigrants from more-developed countries are associated with entrepreneurship among immigrants. However, we do not see evidence that high-skilled immigrants from less-developed countries are associated with entrepreneurship in the local immigrant population, as was the case for entrepreneurship in the native-born population in Table 3. This suggests that results in prior tables describing all and native entrepreneurship are probably not driven exclusively by the immigrants themselves starting businesses.

In Table 5 we investigate the correlation between immigration and entrepreneurship with reversed timing: here immigration measures are the dependent variables, and they are regressed on prior entrepreneurship in the state. Each cell in the table represents a separate regression with a slope coefficient and standard error. If prior entrepreneurship has no relationship with immigration, this table will provide some evidence against the interpretation that immigrants sort into entrepreneurial states, rather than encourage entrepreneurship directly. However, prior entrepreneurship is positively correlated with high-skilled immigrant stocks, in particular from less-developed countries. Entrepreneurship also predicts higher subsequent high-skilled native shares and lower low-skilled native shares. These results are still consistent with a causal effect of immigrants on entrepreneurship, since both might move together over a period of multiple years. But we note that the alternative sorting interpretation cannot be rejected with our results.

Our results are robust to some changes in specification. Table 6 is similar to Table 3 but substitutes population shares for labor force shares. Results are qualitatively similar.

5.2 Immigrants and BDS employment dynamics

The tables in this section investigate associations between immigrant stocks and subsequent state-level business dynamics. Table 7 displays summary statistics for our BDS sample. The average annual state job creation rate is somewhat higher than the job destruction rate, and both vary across states and years. The rate of job creation at the youngest firms looks small, because we define it as jobs created at young firms divided by total employment (of firms with all ages). Job creation rates at the youngest firms are quite high on average, since the share of total job creation that takes place at the youngest firms is 17 percent, while the youngest firms account for only 2.6 percent of total employment. Summary statistics for the immigrant shares and unemployment rates are similar to those in the KIEA analysis, since the analysis years mostly overlap.

Tables 8 and 9 show relationships between labor force shares and several measures of business dynamics at the state level. Table 8 compares immigrant and native labor force shares by skill level. While column 1 does not show a clear relationship between labor force shares and job creation rates, column 2 reveals a positive correlation between high-skilled immigrants and subsequent establishment entry. Subsequent columns show results that are specific to the youngest firms, defined here as those less than one year old. The high-skilled immigrant share is positively associated with job creation at the youngest firms, with the share of state employment at the youngest firms, and with establishment entry rates among the youngest firms. To the extent that young firms signal innovation, the evidence in Table 8 is consistent with our model's prediction that high-skilled immigrants encourage innovation.

We distinguish between immigrants from more-developed and less-developed countries with results in Table 9. The relationships between high-skilled immigrants and business dynamics appear to be driven by immigrants from less-developed countries (although the coefficient estimates for high-skilled immigrants from more-developed countries are somewhat imprecise). This is again consistent with the model's prediction that immigrants with less-transferable human capital from their origins provide more encouragement for innovation.

Table 10 looks at correlations between labor force shares and business dynamics with the reversed timing: here immigration measures are the dependent variables, and they are regressed on prior business dynamics. Each cell in the table represents a separate regression with a slope coefficient and standard error. Prior growth at the youngest firms predicts subsequent growth of the high-skilled immigrant share. Similar to the analysis of entrepreneurship with the KIEA, we conclude that the results are consistent with immigrant labor supply increasing state-level business growth over time, but we cannot completely rule out a role for immigrant sorting in this correlation.

6 Conclusion

Our results suggest that college-educated immigrants, particularly those from less-developed countries, are associated with increased entrepreneurship at the state level. Estimated effects of immigrant labor force shares are stronger than those for native labor force shares, and they hold up when focusing on entrepreneurship among natives (rather than immigrants themselves). We also find evidence that immigrants are associated with state-level business dynamics, especially growth among the youngest firms.

These empirical results are consistent with the immigrant human capital investment model of Duleep and Regets (1999, 2002) and described here. Immigrants are likely to face barriers when transferring human capital acquired in their origin countries into labor force activities at their destination (the U.S. in our context). Immigrants to the U.S. will invest more in human capital in the U.S. when the opportunity cost of doing so is lower, which is the case when their prior human capital does not transfer well (say, those from less-developed countries). Also, immigrants will invest more in human capital in the U.S. when doing so is more productive; for example, college-educated immigrants have already learned how to learn and will likely experience greater ease and productivity in U.S.-based human capital investment. Our findings are consistent with this pattern of immigrant investment tendencies being associated with greater entrepreneurship activity, which may be an indicator for innovation.

Although it is well known that some groups of immigrants are more likely to be self-employed than natives, little is known about how immigrants affect business development in general. A distinguishing feature of our model is that the availability of immigrant labor – given its high propensity to invest in human capital – fosters innovation and business development. That higher shares of college-educated immigrants lead to increased entrepreneurial activity of natives suggests that benefits of immigrants are greater than just their direct innovative activity.

References

Akresh, I. (2007). U.S. Immigrants' Labor Market Adjustment: Additional Human Capital Investment and Earnings Growth. *Demography 44*(4), 865–881.

Aydemir, A. and M. Skuterud (2005). Explaining the Deteriorating Entry Earnings of Canada's Immigrant Cohorts, 1966-2000. *The Canadian Journal of Economics 38*(2), 641–671.

Bates, T. (1996). Determinants of Survival and Profitability Among Asian Immigrant-Owned Small Businesses. In H. Duleep and P. V. Wunnava (Eds.), *Immigrants and Immigration Policy: Individual Skills, Family Ties, and Group Identities*, pp. 150–176. Greenwich, CT: JAI Press.

Cadena, B. C. and B. K. Kovak (2016). Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession. *American Economic Journal: Applied Economics August*(8), 257–290.

Chellaraj, G., K. E. Maskus, and A. Mattoo (2008). The Contribution of International Graduate Students to US Innovation. *Review of International Economics 16*, 444–462.

Chiswick, B. R. (1978). The Effect of Americanization on the Earnings of Foreign-born Men. *Journal of Political Economy 86*(5), 897–921.

Chiswick, B. R. (1979). The Economic Progress of Immigrants: Some Apparently Universal Patterns. In W. Fellner (Ed.), *Contemporary Economic Problems*, pp. 357–399. Washington, D.C.: American Enterprise Institute.

Demombynes, G. M. (2002). Three Ways of Looking at Immigrant Wage Growth: Analysis with the 1993-1998 Current Population Survey. *Institute for Labor and Employment Conference January*.

DeSilva, A. (1997). Earnings of Immigrant Classes in the Early 1980's in Canada: A Re-examination. *Canadian Public Policy/Analyse de Politiques 23*(2), 179–202.

Duleep, H., X. Liu, and M. Regets (2018). Country of Origin, Earnings Convergence, and Human Capital Investment. *GLO Discussion Paper Series* (247).

Duleep, H., M. Regets, S. Sanders, and P. V. Wunnava (2021). *Human Capital Investment: A History of Asian Immigrants and Their Family Ties*. Palgrave Macmillan.

Duleep, H. O. and M. Regets (1992). Some Evidence on the Effect of Admission Criteria on Immigrant Assimilation. In B. Chiswick (Ed.), *Immigration, Language and Ethnic Issues: Canada and the United States*, pp. 410–439. Washington, D.C.: American Enterprise Institute.

Duleep, H. O. and M. Regets (1997). Measuring Immigrant Wage Growth Using Matched CPS Files. *Demography 34*(2), 239–249.

Duleep, H. O. and M. Regets (1999). Immigrants and Human Capital Investment. *American Economic Review May*, 186–191.

Duleep, H. O. and M. Regets (2002). The Elusive Concept of Immigrant Quality: Evidence from 1970-1990. *IZA Discussion Paper no. 631.*

Fairlie, R. W. and B. D. Meyer (2003). The Effect of Immigration on Native Self-Employment. *Journal of Labor Economics 21*(3), 619–650.

Flood, S., M. King, S. Ruggles, and J. R. Warren (2015). *Integrated Public Use Microdata Series, Current Population Survey: Version 4.0.* Minneapolis: University of Minnesota. [Machine-readable database].

Green, D. A. (1999). Immigrant Occupational Attainment: Assimilation and Mobility over Time. *Journal of Labor Economics 17*(1), 49–79.

Green, D. A. and C. Worswick (2012). Immigrant Earnings Profiles in the Presence of Human Capital Investment: Measuring Cohort and Macro Effects. *Labour Economics 19*(2), 241–259.

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

International Monetary Fund (2015). *World Economic Outlook database, April 2015 version*. `http://www.imf.org/external/pubs/ft/weo/2015/01/weodata/download.aspx`, Accessed July 22, 2016.

Jasso, G. and M. R. Rosenzweig (1995). Do Immigrants Screened for Skills Do Better than Family-Reunification Immigrants? *International Migration Review 29*(1), 85–111.

Lalonde, R. J. and R. H. Topel (1991). Immigrants in the American Labor Market: Quality, Assimilation, and Distributional Effects. *American Economic Review 81*(2), 297–302.

Lalonde, R. J. and R. H. Topel (1997). Economic Impact of International Migration and the Economic Performance of Migrants. In M. R. Rosenzweig and O. Stark (Eds.), *Handbook of Population and Family Economics*, pp. 800–850. Elsevier.

Lin, C. (2013). Earnings Gap, Cohort Effect and Economic Assimilation of Immigrants from Mainland China, Hong Kong, and Taiwan in the United States. *Review of International Economics 21*(2), 249–265.

Schoeni, R. F. (1997). New Evidence on the Economic Progress of Foreign-Born Men in the 1970s and 1980s. *Journal of Human Resources 32*(4), 683–740.

Villarreal, A. and C. R. Tamborini (2018). Immigrants' Economic Assimilation: Evidence from Longitudinal Earnings Records. *American Sociological Review 83*(4).

World Bank (2016). *World Bank Open Data GDP per capita (current US dollars)*. `http://data.worldbank.org/indicator/NY.GDP.PCAP.CD`, Accessed July 22, 2016.

Wozniak, A. (2010). Are College Graduates More Responsive to Distant Labor Market Opportunities? *Journal of Human Resources 45*(4), 944–970.

7 Tables

Table 1: Summary Statistics for Entrepreneurial Activity and Labor Force Shares

	Mean	Standard deviation
Entrepreneurship of all workers	.003	(.00097)
Entrepreneurship of native-born workers	.0029	(.00098)
Entrepreneurship of immigrant workers	.0036	(.00368)
Immigrant share	.0956	(.07613)
High-skill immigrant share	.0275	(.02272)
Med-skill immigrant share	.0415	(.03561)
Low-skill immigrant share	.0265	(.02548)
More-developed immigrant share	.0112	(.00768)
Less-developed immigrant share	.082	(.07064)
High-skill native share	.2622	(.0517)
Med-skill native share	.581	(.08353)
Low-skill native share	.0613	(.02586)
High-skill More-dev. immigrant share	.0053	(.00461)
Med-skill More-dev. immigrant share	.0054	(.00416)
Low-skill More-dev. immigrant share	5.3e-04	(.00097)
High-skill Less-dev. immigrant share	.0215	(.01934)
Med-skill Less-dev. immigrant share	.035	(.03292)
Low-skill Less-dev. immigrant share	.0254	(.02512)
Unemployment rate	.0558	(.02181)

NOTES: Data sources are Kauffman Foundation for entrepreneurship and IPUMS for Current Population Survey. State-level annual data. Entrepreneurship and unemployment rate variables cover 1996-2013. Labor force share variables are lagged and cover 1995-2012. Sample size is 918.

Table 2: Entrepreneurship and Lagged State-Year Labor Force Shares

	(1)	(2)	(3)	(4)	(5)
Dep. var.: All entrepreneurial activity					
Immigrant Share	.002				
	(.0021)				
High-skill Immigrant Share		.011**		.011**	.013***
		(.0044)		(.0044)	(.0048)
High-skill Native Share			.0011	.0011	.0022
			(.0012)	(.0011)	(.0029)
Med-skill Immigrant Share					-5.7e-04
					(.0037)
Med-skill Native Share					.0015
					(.0026)
Low-skill Immigrant Share					.0012
					(.0043)
Unemployment rate	.0036	.0033	.0039	.0033	.0033
	(.0026)	(.0024)	(.0026)	(.0024)	(.0024)
Observations	918	918	918	918	918
R^2	.5028	.5085	.5022	.5084	.5072
Dep. var.: Natives' entrepreneurial activity					
Immigrant Share	.0015				
	(.0018)				
High-skill Immigrant Share		.0072*		.0072*	.0093**
		(.0042)		(.0042)	(.0045)
High-skill Native Share			8.6e-04	8.1e-04	.0017
			(.0012)	(.0012)	(.0027)
Med-skill Immigrant Share					-.0022
					(.0031)
Med-skill Native Share					.0012
					(.0023)
Low-skill Immigrant Share					.0038
					(.0034)
Unemployment rate	.0033	.0031	.0035	.0031	.0031
	(.0025)	(.0023)	(.0024)	(.0023)	(.0023)
Observations	918	918	918	918	918
R^2	.4965	.4988	.4962	.4985	.4979

NOTES: Data sources are Kauffman Foundation for entrepreneurship and IPUMS for Current Population Survey. Annual data 1996-2013. Weighted OLS. All specifications include state and year fixed effects. Labor force share variables are one-year lags. Unemployment rates are contemporaneous with entrepreneurial activity measures.

Table 3: Entrepreneurship and Lagged State-Year Labor Force Shares by Immigrant Origin

	(1)	(2)	(3)	(4)
Dep. var.: All entrepreneurial activity				
More-dev. imm. share	-.0073			
	(.006)			
Less-dev. imm. share	.0026			
	(.0021)			
More-dev. high-skill imm. share		.0096		.0088
		(.0094)		(.0093)
Less-dev. high-skill imm. share			.012***	.0106**
			(.0045)	(.0044)
More-dev. med-skill imm. share		-.0185**		-.0162*
		(.0087)		(.0086)
Less-dev. med-skill imm. share			-7.9e-04	-7.6e-04
			(.0027)	(.0028)
More-dev. low-skill imm. share		-.0398		-.0258
		(.0263)		(.0233)
Less-dev. low-skill imm. share			-5.0e-04	1.6e-04
			(.0038)	(.0038)
Unemployment rate	.0036	.0038	.0035	.0034
	(.0026)	(.0025)	(.0024)	(.0024)
Observations	918	918	918	918
R^2	.5038	.5056	.5074	.5089
Dep. var.: Natives' entrepreneurial activity				
More-dev. imm. share	-.0074			
	(.0065)			
Less-dev. imm. share	.0021			
	(.0018)			
More-dev. high-skill imm. share		.0049		.0036
		(.0106)		(.0102)
Less-dev. high-skill imm. share			.0088**	.0075*
			(.0044)	(.0044)
More-dev. med-skill imm. share		-.0151		-.0143
		(.0095)		(.0099)
Less-dev. med-skill imm. share			-.0022	-.0024
			(.0023)	(.0025)
More-dev. low-skill imm. share		-.0354		-.0291
		(.0258)		(.0235)
Less-dev. low-skill imm. share			.0026	.0033
			(.0031)	(.003)
Unemployment rate	.0033	.0035	.0032	.0032
	(.0025)	(.0023)	(.0024)	(.0024)
Observations	918	918	918	918
R^2	.4973	.498	.4984	.4991

NOTES: Data sources are Kauffman Foundation for entrepreneurship and IPUMS for Current Population Survey. Annual data 1996-2013. Weighted OLS. All specifications include state and year fixed effects. Labor force share variables are one-year lags. Unemployment rates are contemporaneous with entrepreneurial activity measures.

Table 4: Immigrant Entrepreneurship and Lagged State-Year Labor Force Shares by Immigrant Origin

	(1)	(2)	(3)	(4)
Dep. var.: Immigrants' entrepreneurial activity				
More-dev. imm. share	.0238			
	(.0189)			
Less-dev. imm. share	4.4e-04			
	(.0063)			
More-dev. high-skill imm. share		.0475*		.0487*
		(.0257)		(.0258)
Less-dev. high-skill imm. share			-.0052	-.0055
			(.0129)	(.0133)
More-dev. med-skill imm. share		8.1e-04		-1.4e-04
		(.0258)		(.0251)
Less-dev. med-skill imm. share			.0011	.0028
			(.0098)	(.0093)
More-dev. low-skill imm. share		.0569		.0486
		(.0807)		(.0845)
Less-dev. low-skill imm. share			.003	.0022
			(.0109)	(.0107)
Unemployment rate	9.2e-04	9.0e-04	.0013	7.8e-04
	(.0075)	(.0075)	(.0075)	(.0077)
Observations	918	918	918	918
R^2	.2614	.2617	.2596	.2593

NOTES: Data sources are Kauffman Foundation for entrepreneurship and IPUMS for Current Population Survey. Annual data 1996-2013. Weighted OLS. All specifications include state and year fixed effects. Labor force share variables are one-year lags. Unemployment rates are contemporaneous with entrepreneurial activity measures.

Table 5: Lagged State-Year Entrepreneurial Activity and Subsequent Labor Force Shares

	(1)	(2)
	Right-hand-side variable	
	Once-lagged	
Dep. Var.	*All entrep.*	*Native entrep.*
Imm. share	.4129	.4803
	(.9609)	(.9176)
High-skill imm. share	1.402***	1.047***
	(.4028)	(.3676)
Med-skill imm. share	-.2224	-.2028
	(.5227)	(.4649)
Low-skill imm. share	-.7667	-.3636
	(.5906)	(.5404)
More-developed imm. share	-.2082	-.2449
	(.1862)	(.1871)
Less-developed imm. share	.8135	.9241
	(.9389)	(.9211)
Avg Ln(GDP) of imm. origins	4.817	-6.369
	(15.31)	(14.43)
High-skill More-dev. imm. share	.0643	-.0212
	(.1262)	(.1277)
Med-skill More-dev. imm. share	-.2072	-.1795
	(.1316)	(.129)
Low-skill More-dev. imm. share	-.0653*	-.0441
	(.0361)	(.0338)
High-skill Less-dev. imm. share	1.417***	1.146***
	(.4112)	(.3699)
Med-skill Less-dev. imm. share	.0911	.0819
	(.4629)	(.4234)
Low-skill Less-dev. imm. share	-.6945	-.304
	(.5771)	(.5283)
High-skill native share	3.118***	2.492**
	(1.209)	(1.173)
Med-skill native share	-1.74	-1.237
	(1.33)	(1.377)
Low-skill native share	-1.79**	-1.735***
	(.7549)	(.6406)

NOTES: Data from Kauffman Foundation and IPUMS. Annual data 1996-2013. N=918. Weighted OLS. Each cell includes the coefficient estimate (and standard error) from a separate regression. All specifications include state and year fixed effects and state-year unemployment rate.

Table 6: Entrepreneurship and Lagged State-Year Population Shares

	(1)	(2)	(3)	(4)
Dep. var.: All entrepreneurial activity				
More-dev. imm. share	-.0099			
	(.0072)			
Less-dev. imm. share	.0026			
	(.0022)			
More-dev. high-skill imm. share		.0061		.0052
		(.0102)		(.0103)
Less-dev. high-skill imm. share			.0143***	.0133***
			(.0046)	(.0046)
More-dev. med-skill imm. share		-.0208**		-.0187*
		(.0106)		(.0105)
Less-dev. med-skill imm. share			-.0031	-.0035
			(.0027)	(.0029)
More-dev. low-skill imm. share		-.0173		-.0025
		(.0218)		(.0217)
Less-dev. low-skill imm. share			.001	.0017
			(.0042)	(.0042)
Unemployment rate	.0037	.004	.0035	.0037
	(.0026)	(.0025)	(.0024)	(.0024)
Observations	918	918	918	918
R^2	.5043	.5045	.5082	.509
Dep. var.: Natives' entrepreneurial activity				
More-dev. imm. share	-.0071			
	(.0074)			
Less-dev. imm. share	.0025			
	(.0019)			
More-dev. high-skill imm. share		.0036		.0023
		(.0108)		(.0105)
Less-dev. high-skill imm. share			.012***	.0115**
			(.0045)	(.0047)
More-dev. med-skill imm. share		-.0172		-.0167
		(.011)		(.0118)
Less-dev. med-skill imm. share			-.0052*	-.0055*
			(.0027)	(.0029)
More-dev. low-skill imm. share		.0017		.0107
		(.0215)		(.022)
Less-dev. low-skill imm. share			.0052	.0056
			(.0036)	(.0036)
Unemployment rate	.0033	.0036	.0032	.0034
	(.0025)	(.0024)	(.0024)	(.0024)
Observations	918	918	918	918
R^2	.4977	.4968	.501	.5011

NOTES: Data from Kauffman Foundation and IPUMS. Annual data 1996-2013. Weighted OLS. All specifications include state and year fixed effects. Population share variables are one-year lags. Unemployment rates are contemporaneous with entrepreneurial activity measures.

Table 7: Summary Statistics for Business Dynamics and Labor Force Shares

	Mean	Standard deviation
Job creation rate	.1505	(.02284)
Job destruction rate	.1376	(.02155)
Establishment entry rate	.1103	(.01909)
Establishment exit rate	.0992	(.01251)
Youngest firms job creation rate	.0259	(.00676)
Share of job creation at youngest firms	.1705	(.02833)
Share of total employment at youngest firms	.0261	(.00677)
Youngest firms establishment entry rate	.0722	(.01629)
Immigrant share	.0925	(.07547)
High-skill immigrant share	.0263	(.02213)
Med-skill immigrant share	.0402	(.03516)
Low-skill immigrant share	.026	(.02562)
More-developed immigrant share	.0111	(.00772)
Less-developed immigrant share	.0785	(.06978)
High-skill native share	.2586	(.05088)
Med-skill native share	.5854	(.08259)
Low-skill native share	.0635	(.02673)
High-skill More-dev. immigrant share	.0052	(.00453)
Med-skill More-dev. immigrant share	.0054	(.00423)
Low-skill More-dev. immigrant share	5.7e-04	(.00103)
High-skill Less-dev. immigrant share	.0203	(.01877)
Med-skill Less-dev. immigrant share	.0335	(.03234)
Low-skill Less-dev. immigrant share	.0247	(.02522)
Unemployment rate	.0548	(.02157)

NOTES: Data sources are Census Bureau for Business Dynamics Statistics and IPUMS for Current Population Survey. State-level annual data. Business dynamics and unemployment rate variables cover 1995-2012. Labor force share variables are lagged and cover 1994-2011. Sample size is 918.

Table 8: Business Dynamics and Lagged State-Year Labor Force Shares

Dep. var.	(1) Job creation rate	(2) Establishment entry rate	(3) Youngest firms job creation rate	(4) Share of job creation at youngest firms	(5) Share of total employment at youngest firms	(6) Youngest firms establishment entry rate
High-skill immigrant share	-.0232	.078*	.0615***	.3366***	.0623***	.0911**
	(.0601)	(.044)	(.0206)	(.115)	(.0208)	(.0391)
High-skill native share	.0324	.0274	.0211**	.0529	.0211**	.0298
	(.0321)	(.0298)	(.0093)	(.058)	(.0093)	(.0224)
Med-skill immigrant share	-.0606	-.0201	.0019	.0802	7.6e-04	-.0031
	(.0536)	(.0386)	(.0189)	(.1114)	(.0193)	(.0321)
Med-skill native share	.049	.0118	.0179**	.0162	.0174**	.0197
	(.0347)	(.0248)	(.0086)	(.049)	(.0087)	(.0193)
Low-skill immigrant share	.0232	-.0084	.0358**	.1302	.0371**	.0247
	(.0564)	(.0435)	(.0167)	(.087)	(.0169)	(.0356)
Unemployment rate	-.0529	-.0753**	-.0071	.0301	-.009	-.0835***
	(.0524)	(.0376)	(.0127)	(.0601)	(.0129)	(.0287)
Observations	918	918	918	918	918	918
R^2	.8891	.9369	.8829	.7461	.8814	.939

NOTES: Data from Census BDS and IPUMS. Annual data 1995-2012. Weighted OLS. All specifications include state and year fixed effects. Labor force share variables are one-year lags. Unemployment rates are contemporaneous with BDS measures.

Table 9: Business Dynamics and Lagged State-Year Labor Force Shares by Immigrant Origins

Dep. var.	(1) Job creation rate	(2) Establishment entry rate	(3) Youngest firms job creation rate	(4) Share of job creation at youngest firms	(5) Share of total employment at youngest firms	(6) Youngest firms establishment entry rate
More-dev. high-skill immigrant share	.0314	.006	.0259	.0612	.0237	.0344
	(.1037)	(.08)	(.0396)	(.2505)	(.04)	(.0638)
Less-dev. high-skill immigrant share	-.0449	.1008**	.0554***	.37***	.057***	.1018***
	(.0487)	(.0413)	(.0199)	(.115)	(.0201)	(.0368)
More-dev. med-skill immigrant share	.0598	.041	.0219	.0752	.0185	.0017
	(.1113)	(.0674)	(.0388)	(.2427)	(.0401)	(.0546)
Less-dev. med-skill immigrant share	-.1194***	-.0473	-.0227	.0286	-.0233	-.0307
	(.0395)	(.0424)	(.0186)	(.0985)	(.0191)	(.0306)
More-dev. low-skill immigrant share	.2282	-.0341	.0252	.0493	.0237	.1495
	(.3659)	(.2613)	(.1206)	(.6239)	(.118)	(.2128)
Less-dev. low-skill immigrant share	-.0165	-.017	.0208	.1133	.0223	.0061
	(.0582)	(.0355)	(.0147)	(.093)	(.015)	(.0268)
Unemployment rate	-.0509	-.0741**	-.0055	.0349	-.0073	-.0822***
	(.0523)	(.0374)	(.0129)	(.0601)	(.0131)	(.0287)
Observations	918	918	918	918	918	918
R^2	.8889	.9369	.8825	.7461	.881	.9391

NOTES: Data from Census BDS and IPUMS. Annual data 1995-2012. Weighted OLS. All specifications include state and year fixed effects. Labor force share variables are one-year lags. Unemployment rates are contemporaneous with BDS measures.

Table 10: Lagged Business Dynamics and Subsequent Immigrant Labor Force Shares

(1)	(2)	(3)	(4)	(5)
Dependent Variable				
All imm.	High-skilled imm.	Low-skilled imm.	More-developed imm.	Less-developed imm.
Lagged job creation rate				
-.0904	-.0488	.007	.0308*	-.0772
(.0845)	(.042)	(.0466)	(.0174)	(.0806)
Lagged youngest firms job creation rate				
.3568	.3877***	-.0264	.0486	.4254
(.3553)	(.1411)	(.1503)	(.0551)	(.3899)
Lagged share of job creation at youngest firms				
.1028*	.0887***	-.013	-9.7e-04	.1065*
(.0537)	(.0216)	(.032)	(.0085)	(.0571)
Lagged job destruction rate				
.0321	-.0417*	.0759**	-.0066	4.6e-04
(.0615)	(.0221)	(.0339)	(.0135)	(.0661)
Lagged share of total employment at youngest firms				
.3586	.3822***	-.0195	.0464	.4258
(.3574)	(.1414)	(.1522)	(.0554)	(.3929)
Lagged establishment entry rate				
-.0843	.0782	-.1639**	-.0028	-.0044
(.1652)	(.0985)	(.0802)	(.0347)	(.1834)
Lagged youngest firms establishment entry rate				
.2265	.2112*	-.1303	-.012	.3318
(.1937)	(.1175)	(.0973)	(.0401)	(.2202)
Lagged establishment exit rate				
-.1352	-.0036	-.0919	-.0821***	-.071
(.1663)	(.083)	(.0854)	(.0226)	(.1789)

NOTES: Data from Census BDS and IPUMS. Annual data 1995-2012. N=1020. Weighted OLS. Each cell includes the coefficient estimate (and standard error) from a separate regression. All specifications include state and year fixed effects and unemployment rate.