“Misfits”, “Stars” and Immigrant Entrepreneurship

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Abstract

Prior research has shown that immigrants are more likely than natives to become entrepreneurs, and that entrepreneurs are disproportionately drawn from the extremes of the ability distribution. Using a large panel of US residents with bachelors’ degrees in scientific fields, we ask whether higher rates of entrepreneurship among immigrants can be explained by their position on the ability spectrum, and establish four new facts about science-based and immigrant entrepreneurship. First, in this sample, an immigrant entrepreneurship premium exists only in science-based entrepreneurship. Second, this premium persists after controlling for ability (measured by paid-employment wage residuals.) Third, a U-shaped relationship between ability and entrepreneurship exists only in non-science entrepreneurship; for science entrepreneurship, the relationship is increasing. Finally, the immigrant premium in science entrepreneurship is largest among immigrants with non-US degrees and those from non-English speaking or culturally dissimilar countries. Stated preferences for self-employment do not explain the immigrant premium. The results suggest that immigrants may on average have higher levels of unobservable skills related to entrepreneurship.

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1. Introduction

A growing literature in entrepreneurship has found that immigrants are more likely than the native-born to start new businesses. In addition, a number of studies have shown that "stars" (individuals at the very top of the wage distribution) and "misfits" (those at the bottom) are more likely to become entrepreneurs.[1] Research also suggests that immigrants may be overrepresented at the extremes of the ability distribution.[2] This paper asks whether the documented higher rates of entrepreneurship among immigrants – an immigrant entrepreneurship premium – are explained by immigrants' positions at the extremes of the ability distribution. That is, do immigrants have higher rates of entrepreneurship because they are more likely to be "stars" and/or "misfits"? Or is there another immigrant characteristic besides ability—for example, a taste for being one's own boss, or alertness to entrepreneurial opportunities—that predicts entrepreneurship along the entire ability range?

In order to answer this question, we expand upon prior studies in two main ways. First, we assess whether the U-shaped relationship between wages and entrepreneurship documented in prior studies could reflect heterogeneity in types of entrepreneurship. Thus, the firms founded by entrepreneurs drawn from the bottom of the ability distribution may be more likely to be non-technology-intensive enterprises with relatively low skill requirements. The "star" entrepreneurs, on the other hand, may found high-tech, R&D-intensive start-ups. Given that immigrants are more likely than natives to have degrees in Science, Technology, Engineering and Math

[1] On immigrant entrepreneurs, see e.g. Borjas (1986), Fairlie (2008), Hart and Acs (2011). On the U-shape in wages, see e.g. Hamilton (2000), Hipple (2004), Poschke (2013), Astebro *et al.* (2011). The latter source uses the term "misfits."

[2] For example, immigrants who entered on student or temporary visas have been shown to have higher rates of education and patenting (Hunt 2011). At the other extreme, Ferrer and Riddell (2008) show that immigrants have lower returns to education and to work experience than natives.

(STEM), immigrant entrepreneurs may be more likely to be stars.[3] Specifically, in this paper we demonstrate the importance of distinguishing between “science” entrepreneurship and “non-science” entrepreneurship, using a sample of individuals with at least a bachelor’s degree in science drawn from the NSF’s SESTAT database. We introduce a novel definition of entrepreneurship in science based on detailed information on worker’s activities on the job.

Secondly, we use wage residuals in past employment rather than wages as our measure of ability. Our data set allows us to control for a number of relevant characteristics in the wage equation, including detailed information on field of study of highest degree. This allows us to ask a slightly different question: are individuals who are paid a lot less (or a lot more) than workers with comparable characteristics more likely to become entrepreneurs? For immigrants, being paid less than natives with similar observable characteristics may reflect differences in ability, but also discrimination or mismatch in the labor market, or other factors.

Our analysis replicates the U-shaped relationship between entrepreneurship and ability documented in prior studies for non-science entrepreneurship. Non-science entrepreneurs are disproportionately drawn from the extremes of the wage residual distribution. We find that immigrants and natives are similarly likely to enter non-science entrepreneurship, and that the U-shape in non-science entrepreneurship is almost identical for natives and immigrants.

The picture is quite different, however, when it comes to science entrepreneurship, which pulls more people from the top of the wage residual distribution. This is consistent with the idea that barriers to entry are higher in science entrepreneurship. We estimate a large immigrant premium in science entrepreneurship, even after controlling for the distribution of wage residuals in prior employment. This implies that immigrants enter science entrepreneurship at higher rates for reasons *other* than ability or mismatch as measured by prior wage residuals. Interestingly, the

[3] Hunt and Gauthier-Loiselle (2010).

immigrant premium in entrepreneurship is not explained by a taste for being one's own boss, as measured by responses to survey questions about preferences for employment: immigrants are significantly more likely to enter entrepreneurship, even after controlling for their stated preferences for self-employment.

Finally, we document the fact that the immigrant premium in science entrepreneurship is driven by immigrants from non-English speaking countries, immigrants from countries that are culturally different from the US, and immigrants who did not receive their highest degree in the US. We also observe that these three groups of immigrant entrepreneurs are overrepresented at the bottom of the distribution of wage residuals relative to natives. This fact suggests that communication and cultural barriers may lead employers to underestimate the ability of some immigrants who then go on to establish new firms. However, the fact that the immigrants' advantage in science entrepreneurship for these three groups persists after controlling for ability in paid employment suggests that other potential factors may also explain the observed immigrant premium.

This paper contributes to the literature on science entrepreneurship by showing that the previously established U-shape in entrepreneurship and ability is not apparent in science-based businesses. These findings contribute also to the literature on immigrant entrepreneurship by demonstrating the importance of distinguishing between science and non-science entrepreneurship: our results suggest that, at least among individuals with higher education in science, the immigrant premium only exists for entrepreneurship in science-related businesses. The fact that this premium is largest for more culturally distant immigrants warrants further investigation, in particular as it relates to the concepts of alertness, information, and immigrant entrepreneurship.

We begin by introducing a conceptual framework grounded in the prior literature that yields testable hypotheses. We then describe our dataset, analyses and findings.

2. Hypotheses about Immigrant and Science Entrepreneurship

2.1. Entrepreneurship and ability

In this conceptual framework, we think it useful to distinguish between three different types of abilities. First, we consider observable human capital characteristics such as education and experience that may increase productivity in all kinds of jobs. We call these characteristics *H*. Second, we consider abilities and skills (which we will call *M)* that increase productivity particularly in paid employment—for instance teamwork skills and the ability to follow directions and accomplish tasks in a timely fashion. Third, we consider skills and abilities that are particularly useful for entrepreneurship (denoted by *R* for resourcefulness*)*.[4]

Thus, entrepreneurship has been conceptualized as arising from a number of characteristics not captured by observable human capital measures (*H*) or by other skills rewarded in paid employment (*M*). Kirzner (1972, 1979) introduced the concept of "alertness," that is, the ability to recognize and exploit opportunities for profit created by the mis-pricing of goods. Kirzner argued that this alertness stands in contrast to the Schumpeterian vision of the entrepreneur who creates opportunities by introducing new products or methods of production (Kirzner 1999). A similar concept is that of knowledge corridors, or privileged access of certain individuals to information about prices and costs, technological developments, or arbitrage opportunities that enable those privy to the information to exploit the information via entrepreneurship (Hayek 1945, Venkataraman 1997). Shane (2000) draws on this idea to argue that differences across individuals in prior knowledge and experience help explain differences in the ability to recognize

[4] Jovanovic (1994) develops a model that generates predictions about which types of workers become entrepreneurs depending on the correlation between skills related to managing others (x) and those related to working for a wage (y).

entrepreneurial opportunities. In scientific entrepreneurship requiring radical innovation, slightly different skills may be necessary to be able to make sense of widely dispersed and vague ideas (see Moller 2010). Since the *R* abilities are typically difficult to measure, empirical studies on the relationship between *R* and entrepreneurship are scarce.

Previous research examined the empirical relationship between human capital (*H*) and entrepreneurship and found higher rates of entrepreneurship at both ends of the observed ability spectrum. Thus, entrepreneurship rates have been shown to have a U-shaped relationship to education levels: higher for those with low and high *education* levels but lower for those with more average education levels.[5] The same U-shaped relationship has been identified between *experience* and entrepreneurship (Rider *et al.* 2013) and between *wages* in previous paid employment and entrepreneurship (Poschke 2013, Elfenbein *et al.* 2010, Braguinsky *et al.* 2012).[6] Wages in paid employment reflect a combination of observable human capital (*H*) and the *M* abilities that increase productivity in paid employment but are not observable to researchers.

This paper first aims to estimate the relationship between *M* abilities in paid employment and entrepreneurship. Understanding this relationship can help to identify those workers who are most likely to leave paid employment. This is important for policymakers interested in targeting future entrepreneurs (Roach and Sauermann 2015). We make assumptions about the relationship between human capital (*H*), unobservable abilities that are important in entrepreneurship (*R*) and unobservable, specifically paid-employment abilities (*M*) to derive testable hypotheses on the

[5] Poschke (2013) finds this using data from NLSY but also reports this from calculations he did from data used by Borjas and Bronars 1989, Hamilton 2000, and Hipple (2004) among others; Astebro et al. (2011) has also found a bimodal relationship between entrepreneurship and education.

[6] While Braguinsky *et al.* (2012) do not characterize their evidence as showing the relationship to be U-shaped, their table shows a clear U-shaped relationship for older scientists and a J-shaped relationship for younger ones.

relationship between M and entrepreneurship. We test these hypotheses empirically by using wage residuals in paid employment to measure M abilities. Using wage equations, we separate out the impact of measureable human capital skills (H) from M abilities.

We predict that we will find that many people who become entrepreneurs will come from the bottom of the paid-employment ability continuum when measured using wage residuals; since these people are rewarded less than workers with similar observable characteristics, they may believe that they are underpaid relative to their abilities — the "grass is greener" phenomenon. The colorful terms "hobo" and "misfit" have been applied to these lower-ability entrepreneurs, but another way of thinking of them is as people with low opportunity costs of leaving paid employment for entrepreneurship due to being paid less than one would predict based on their observable characteristics.[7] Thus, we will test:

Hypothesis 1: Rates of entry into entrepreneurship increase as wage residuals become more negative.

The empirical literature has shown that at high human capital or wage levels, we also see a high proportion of people entering entrepreneurship. This would be expected if people who are highly skilled in paid employment (M) are also highly skilled in entrepreneurship (R). Lazear (2005) argues that those with a high level of a variety of abilities – referred to by Lazear as "jacks-of-all-trades" – will find their broad skills particularly useful in starting one's own business. "Stars" may enter entrepreneurship in order to capture their entire marginal product or because of their high return to entrepreneurship (e.g. Elfenbein *et al.* 2010, Murphy *et al.* 1991). Those at the top of the ability distribution may also be those best able to both generate innovative ideas and evaluate their commercial viability (Braguinsky et al. 2012). Once again, we may think of these individuals as those who have a low opportunity cost of leaving paid employment

[7] E.g., Astebro *et al.* (2011), Astebro and Thompson (2011).

relative to the potential gains from entrepreneurship, even though the absolute returns to paid employment may be high.

Here, we use the term "star" to refer to individuals in the top 10% of the distribution of wage residuals in paid employment among a nationally representative sample of everyone with a bachelor's degree in any scientific field. This usage differs from an extensive literature in the social sciences that has studied the contribution of academic star scientists to the creation of science-based firms (see for example seminal work by Zucker *et al*. 1998; Zucker *et al*. 2002). Those papers typically define stars based on their extensive scientific research output, such as number of articles, patents, or citations, resulting in a rarified group that typically includes less than 1% of PhD-level scientists in a particular field (many of whom never become full-time entrepreneurs), and thus a far smaller percentage than of our sample which includes all those with bachelors in science.

If those with particularly high abilities tend to have both M and R abilities, then we also predict that:

Hypothesis 2: Entry into entrepreneurship is increasing in positive wage residuals.

Our theory combines aspects of previous work on the relationship between ability and entrepreneurship. Low *opportunity costs* make those with low levels of M more likely to become entrepreneurs as in Elfenbein et al. 2010. Additionally, at low levels of M, endowments of R are relatively weakly correlated with M, which is especially likely to be true for *"misfits"* (Astebro et al. 2011). Finally, those with high levels of both M and R are "*Jacks-of-all-trades*" who also enter entrepreneurship (Lazear 2005). When both the "misfit" and the "Jack-of-all-trades" phenomena occur, only those with near-average abilities in paid employment find it more advantageous to remain there, as in Poschke (2013).

Second, we attempt to test whether the relationship between *M* abilities and entrepreneurship differs between immigrants and natives. Previous research has documented higher rates of self-employment among immigrants than among the native-born, particularly in the US and in high-technology enterprises.[8] Seminal work by George Borjas (1986) found that immigrants had significantly higher rates of self-employment than natives with similar observable characteristics, and the likelihood of self-employment increased the longer the immigrant had been in the US and the later the cohort of arrival. Fairlie (2008) found that foreign-born are 1.8 percentage points more likely to own a business than natives in the 2000 Census, while a panel data set created from the Current Population Survey indicated that immigrants contribute to business formation at a higher rate than natives.

Higher rates of business creation among immigrants are particularly observed in the high-technology sector. In a survey of the high-tech sector, Hart and Acs (2011) find that 16% of the companies in their sample reported at least one founder who was foreign-born. Wadhwa et al. (2007) shows that 25% of a sample of 144 technology companies founded between 1995 and 2005 had foreign born CEO's or CTO's. Anderson and Platzer (2006) found that in the period 1990-2005, immigrants founded 40 percent of U.S. public venture-backed companies in high technology. Finally, using the National Survey of College Graduates data, Hunt (2011) showed that, controlling for education, immigrants are more likely to have started a firm with more than 10 employees in the past 5 years compared to natives.

Why are immigrants more entrepreneurial than natives? One possibility is that immigrants are more likely than natives to be paid poorly because the value of their human capital is not accurately perceived by employers or because they have *M* skills useful in other cultures but less

[8] Fairlie and Lofstrom (2013) and Kerr and Kerr (2016) summarized the literature on immigrant entrepreneurship; in two recent reviews, Kerr (2013) and Nathan (2014) focused on the contribution of high-skilled immigrants to innovation and entrepreneurship.

useful in the US. They are thus likely to have large negative measured wage residuals and simply because of this lower valuation in paid employment they will be more likely to enter entrepreneurship. We expect this to be especially true for those who are least like natives in the sense of receiving their education outside of the US, not coming from an English-speaking country, or coming from a culturally dissimilar country. Therefore, a related hypothesis would be:

Hypothesis 3: Immigrants – especially those receiving their education outside of the US, not coming from an English-speaking country, or coming from a culturally dissimilar country – will have disproportionately large negative wage residuals and as a result will enter entrepreneurship.

An alternative hypothesis arises from the fact that immigrants are likely to have higher entrepreneurial abilities (R) than natives, irrespective of their levels of M, for numerous reasons. First, it is plausible that the different prior experiences of immigrants relative to natives predispose immigrants to recognize some entrepreneurial opportunities that go unrecognized by natives, consistent with the alertness or knowledge corridor theory of entrepreneurship. Hart and Acs (2011) suggest that "immigrants may be more "alert" in the Kirznerian sense than the native born" (p. 118). Yuengert (1995) found that immigrants who became self-employed tended to come from countries with more self-employment, and Akee et al. (2007) found that self-employed immigrants in the US often had pre-migration self-employment experience in their home country. Together, these articles suggest that immigrants have had more involvement or exposure to self-employment. Jaeger et al. (2010) find that individuals' who tend to migrate have more risk tolerance, while we had already learned that risk tolerance is associated with entrepreneurship. Finally, the close social networks of immigrants from specific countries and areas may confer upon them particularly strong advantages in certain sectors of entrepreneurship. For instance, Chung and Kalnins (2006) study Gujarati immigrants in the U.S. lodging industry and document the importance of social capital within ethnic groups in promoting the survival of motels and similar establishments.

If this is the case, then we would predict that:

<u>Hypothesis 4</u>: Immigrants at all levels of paid-employment ability (M) will have higher levels of entrepreneurship than natives.

A final reason that immigrants may have higher levels of entrepreneurship is that they may have stronger preferences for self-employment. Roach and Sauermann (2015) show that higher risk tolerance, stronger preferences for autonomy, commercializing research and managerial activities are associated with an *interest* in becoming a start-up founder among science and engineering Ph.D. students in the U.S. Indeed, the mere fact that immigrants have left their home countries suggests a heightened preference for change and independence. Recall that Jaeger et al. (2010) showed that immigrants have higher risk tolerance than natives. We would thus predict that:

<u>Hypothesis 5</u>: Controlling for preferences for self-employment, immigrants and natives will have similar entrepreneurship rates.

Finally, we ask how the relationship between M and entrepreneurship may differ for science entrepreneurship compared to non-science entrepreneurship.

The barriers to entry into science-based entrepreneurship are in most cases higher than the barriers to entry into non-science entrepreneurship. Science entrepreneurship may require the creativity and imagination, not to mention the ability to raise financing, necessary to develop a marketable scientific idea which would require a minimum level of R; only levels of R greater than this minimum level would pay a return. As a result, we would not expect to see the “misfit” phenomenon in science entrepreneurship. Findings by Stuart and Ding (2006) support this hypothesis. They show that a high publication and patent record, having a Ph.D. from and working in a prestigious university are associated with a greater likelihood that academic life scientists become entrepreneurs in science. Hunt (2011) shows that immigrants with a bachelor degree in science retain their advantage in entrepreneurship even after controlling for field of study, suggesting that they may be endowed with better “quality” in science-based tasks (Kerr 2013). Thus, those with higher levels of R – and therefore higher levels of M if R and M are positively correlated – are more likely to become entrepreneurs in science.

Moreover, science entrepreneurship is likely to require high levels of all skills, so be correlated with high levels of both M and R abilities. For instance, Murray (2004) identifies scientists’ social capital a significant factor contributing to entrepreneurship, and D’Este and Perkmann (2011) find that academic scientists found spin-offs to commercialize their knowledge. These papers suggest that scientists with high levels of ability in paid employment (M) are more likely to enter science entrepreneurship.

Therefore, it seems most likely that:

Hypothesis 6: Rates of science entrepreneurship increase as wage residuals become larger (more positive).

In the next section, we describe the dataset we use to test these hypotheses about the relationship between wage residuals from paid employment – which capture skills in paid employment not due to standard observable human characteristics – and the tendency for both natives and immigrants to enter science-based versus non-science based entrepreneurship.

3. Data

3.1. SESTAT database

This analysis uses the National Science Foundation's SESTAT database of more than 250,000 individuals observed between 1993 and 2010. SESTAT includes people in the US with a bachelor's degree or higher in some way connected to science or engineering – either due to their job or due to one of their degrees – and follows them through several waves of surveys. Other studies of entrepreneurship using SESTAT include Elfenbein, Hamilton and Zenger (2010), Hunt (2011), Braguinsky, et al. (2012), Ohyama (2011) and Gort and Lee (2007).

SESTAT is collected by the National Science Foundation (NSF) and is the most comprehensive database on the employment, educational, and demographic characteristics of U.S. scientists and engineers available. It includes only people who have science, engineering, technical, or math (STEM) or related degrees or who have worked STEM occupations. The biennial panel nature of the data allows researchers to follow scientists and engineers over time. The 1993-2010 waves together contain 539,565 observations on 260,512 respondents.

Individuals included in SESTAT reside in the United States during the survey reference period, are less than seventy-five years old, and have a bachelors' degree or higher. These individuals have degrees in or work in the fields of computer and math sciences, life sciences, physical sciences, social sciences, engineering, health, or technology (STEM).

SESTAT is based on three NSF surveys. First, its core is the National Survey of College Graduates (NSCG) which (through 2010[9]) created a new panel each decade of scientists with at least a bachelor's degree and followed these people through the decade. Specifically, the SESTAT waves we use are from two NSCG panels, college graduates drawn from the 1990

[9] Starting in 2013, new SESTAT entrants are drawn from the American Community Survey and added each survey year. The NSRCG discussed below has been discontinued.

Census (the 1993-99 panel) and from the 2000 Census (2003-10 panel) who have degrees in science or worked in science occupations in the Census year. SESTAT thus does not include those without STEM degrees who work in STEM jobs but had not been in these jobs in the Census year.

Second, SESTAT then oversamples PhDs by adding in people in the longitudinal Survey of Doctorate Recipients (SDR) and following them through both decades (SDR waves used here are from 1993, 1995, 1997, 1999, 2001, 2003, 2006, 2008 and 2010).[10] The SDR in turn samples respondents from the NSF's Survey of Earned Doctorates, which captures everyone obtaining doctorates in STEM fields from US institutions of higher education.

Finally, through these two decades, subsamples of new graduates from the National Survey of Recent College Graduates (NSRCG) were added to the NSCG panel. The NSRCG sampled individuals who received a science, engineering or health bachelor's or master's degree in the previous two to three academic years. The SDR and NSRCG parts of SESTAT thus do not include those who received their degrees abroad. However, the SDR and NSRCG respondents are a minority of SESTAT: 53% of the observations in our sample come from the NSCG, which includes those with foreign degrees.

Our analysis is based on the 1990s SESTAT panel, which includes 4 waves – 1993, 1995, 1997, and 1999 – and the 2000s panel which also includes 4 waves – 2003, 2006, 2008 and 2010. Since PhDs are followed through both decades, some of them are observed in more than four waves.

SESTAT collects information on education, employment including labor force status, job and employer characteristics, work activities and training, and comprehensive demographic information on gender, race/ethnicity, marital status, children, citizenship and immigration

[10] Note that the weights allow us to deal with biases that might derive from this over-sampling.

status. There are some relevant differences in the 1990s and 2000s surveys and panel. First, an NSF review indicated that the self-employed were being under-reported in the 1990s because of the order of the choices given for "employer type." This was rectified in the following surveys beginning with the 2003 survey. Second, in the 2000s the target population was enlarged to include people with health or other "science and engineering-related" education and occupations. Our analysis does not concern time trends in entrepreneurship, so these differences should not bias our results. We do include survey year dummies in all analyses, and this will pick up any difference across surveys due to these compositional factors as well as time-related factors.

SESTAT presents several advantages for the study of immigrant scientists' transitions from paid employment to science and non-science entrepreneurship. First, detailed information on self-employment status and whether a business is incorporated allow us to minimize error in the measure of entrepreneurship. Second, the longitudinal dimension allows linking individuals' earnings in paid employment to their subsequent self-employment status. Third, SESTAT contains detailed information on field of study and place of highest degree (US or abroad). Fourth, it includes information on job and work activity, which are used to define science entrepreneurship. Other data sets that are large enough to be used to study entrepreneurship, for instance the CPS, Census, American Community Survey (ACS) and NSCG, satisfy some but not all of these criteria.[11]

3.2. Key Variables

[11] More specifically, the Merged Outgoing Rotation Groups of the CPS follow the same individuals for 16 months but do not provide information on field of degree, work activity and place of highest degree. The NSCG and the American Community survey contain information on field of bachelor degree but do not have a longitudinal dimension. Kerr and Kerr (2015) propose a data platform based on the Longitudinal Employer-Household Dynamics (LEHD). While the depth of the data is impressive, the LEHD does not identify firms' founders and owners. The authors' definition of entrepreneurship is based on the initial earnings of employees who work in newly entered firms, which may lead to measurement error.

Throughout this study, we define immigrants as individuals who were born outside the United States and did not migrate during their childhood. We include only individuals who are employed full-time. We define as entrepreneurs people who are self-employed and working for an incorporated business, following Lazear (2004). We prefer this definition to "all self-employed" because those who are self-employed and incorporated have started or intend to start a new business, which is an important contributor to economic growth. Given our highly educated sample, the self-employed non-incorporated may include people such as individual independent health providers or consultants working on their own. We also show later that those who are self-employed but not incorporated are rarely working in science-related endeavors.

Within the set of self-employed incorporated entrepreneurs, we further refine our measure by dividing them into science entrepreneurs and non-science entrepreneurs. While previous literature defined science entrepreneurship based on the closeness of the job to the field of highest degree (Braguinsky et al., 2012), we use detailed information on occupation, primary and secondary work activity. Science entrepreneurs include those self-employed (incorporated) whose occupation is given as a field within science, or whose occupation is "management" but their primary or secondary work activity relates to science. Of the possible work activity categories, we consider the Design of Equipment, Processes, Development, Computer Applications, Programming, Basic research, and Applied Research as related to science. Science entrepreneurship expressly excludes people in professional services, most of whom are doctors or health professionals in private practices. We categorize these and all others not doing expressly science-related work as "Non-science entrepreneurs". More information on the specific definition of science entrepreneurship is given in the Appendix.

Previous studies that have analyzed the empirical relationship between ability in paid employment and entrepreneurship used wages or education as a measure of ability. Here, we measure ability in paid employment primarily in terms of wage residuals from a standard wage equation.[12] If wages accurately reflect ability in paid employment, the residuals in a wage equation measure ability characteristics valuable to the employer, unobserved by us but observed (and paid for) by the employer. However, wages may not accurately capture ability in paid employment if workers are mismatched to their job or discriminated against, which may occur more frequently for immigrants. Negative wage residuals would capture whether they were underpaid relatively to their productive characteristics. We refer to workers with wage residuals at the top of the distribution—those being paid a lot more than workers with the same observable characteristics—as "stars"; we use the term "misfits" to refer to workers who are at the bottom of the distribution of wage residuals—those who are paid substantially less with respect to workers with the same characteristics.

To calculate wage residuals, we first estimated a (log) wage equation on the sample of natives working in full-time paid employment using ordinary least squares (OLS). Control variables included highest degree, field of highest degree, race, age (linear, squared and cubic), gender, marital status, experience (linear, squared and cubic), calendar year dummies, region of residence dummies and interaction terms between calendar year and region of residence. We calculate wage residuals by applying this equation to all people in our sample (i.e. including immigrants).

3.3. Summary statistics

[12] Carnahan *et al.* (2012) also used wage residuals to study the relationship between ability in previous employment and entrepreneurship.

In the 1993-2010 SESTAT, on average 9.28% of workers are classified as entrepreneurs according to our definition (self-employed and incorporated) and an additional 4.76% are self-employed but not incorporated. While the rate of total self-employment is higher among immigrants than among natives (15.59% compared to 13.73%), this differs depending on whether the self-employment is incorporated. Table 1 shows that immigrants have substantially higher likelihoods of being entrepreneurs (self-employed incorporated), where 11.07% of foreign-born were entrepreneurs compared to 8.93% of natives, which translates into immigrants being 24% more likely than native to be entrepreneurs. In contrast, immigrants are 6% (0.28 percentage points) less likely than natives to be self-employed and non-incorporated.

We are most interested in those entrepreneurs (self-employed incorporated) whose new ventures are science-based, i.e. science entrepreneurship. In results not shown, we find that those self-employed in science are about three times more likely to be incorporated than those self-employed non-science (compare 2.41 and 0.72). Seen a different way, those who are self-employed incorporated are about 70% more likely to be in a science-related business than those who are self-employed non-incorporated.

The difference between natives and immigrants is far more striking in science entrepreneurship (self-employed incorporated) than in non-science entrepreneurship (Table 1). Immigrants are about twice as likely as non-immigrants (4.14 v. 2.08 percentage points) to be engaged in science entrepreneurship, while they are equally likely to be engaged in non-science entrepreneurship (with both at 6.85%). Even among those who are self-employed and unincorporated, we are more likely to find immigrants as science entrepreneurs than natives, although these rates are tiny.

Many of our key results investigate whether the likelihood of a person *entering* entrepreneurship from paid employment – i.e. being observed in entrepreneurship after having been in paid employment in the previous survey – is associated with their wage residuals from that previous paid employment. This requires using the longitudinal aspect of our data. To do so, we include only people who were observed (at least) twice, the first while working in paid employment (we refer to this sample as "two-period sub-sample"). People first seen in the 1999 (for all but doctorates) or in the 2010 waves of the sample could not be included because they were never observed in a subsequent survey.[13] We excluded people from the sample if they were already entrepreneurs the first time they appear in the sample or if they had recently been entrepreneurs. We also excluded people if they were observed in paid work in a given year, were not observed in the next survey year, but were observed as entrepreneurs in a later survey wave (4-7 years in the future). Table 2 gives the size of the two-period sub-sample and the average likelihood of becoming an entrepreneur during the next period in this sample. There are approximately 57% as many observations as in the earlier sample for both natives and immigrants. Not surprisingly, the probabilities of *becoming* an entrepreneur from one period to the next are much smaller than the probabilities of *being* an entrepreneur at any particular time. However, the differences between immigrants and natives are the same: immigrants overall are more likely than natives to be entrepreneurs (self-employed incorporated). This averages the fact that immigrants are substantially more likely to become science entrepreneurs, but not more likely to become non-science entrepreneurs.

To put these results in context, we compare them with the rates of entrepreneurship previously estimated in the literature. We restrict our comparison to studies that analyzed

[13] However, those with PhDs surveyed in the SDR were continued from the 1990s to the 2000s and therefore were not dropped if first seen in 1999.

nationally representative data such as Census, CPS and NSCG. Borjas (1986) calculated that among white men aged 18-64, 16.5 percent of immigrants and 11.7 percent of natives were self-employed in the 1980 Census, compared to our 15.6% and 13.7% respectively in a later sample that includes women and blacks, both of whom have lower entrepreneurship rates. Fairlie (2008) found that 9.7 percent of immigrants and 9.5 percent of natives were business owners in the 2000 Census. Both Borjas (1986) and Fairlie (2008) analyzed entrepreneurship rates for all education groups and included those that are self-employed and non-incorporated among the entrepreneurs. Looking at a cross-section of individuals with a bachelor degree from the 2003 NSCG, Hunt (2001) showed that 0.8 percent of immigrants and 0.6 percent of natives started a firm with more than 10 workers during the 1998-2003 period. Her definition of entrepreneurship is narrower than ours and she included BAs from all fields. In sum, all these studies consistently showed that immigrants are more entrepreneurial than natives. The levels of entrepreneurship estimated in these studies may differ from the ones estimated in this paper due to differences in sample selection and definition of entrepreneurship. Turning to rates of business formation in previous research, Fairlie (2008) estimated that business formation rates per month among immigrants and natives in the 1996-2007 CPS were respectively 0.35 and 0.27 percent. He also found that 17 percent of all new business owners in the United States were immigrant.

4. Entrepreneurship and ability in paid employment: empirics

In this section, we explore the relationship between an individual's entrepreneurial behavior and his/her ability in previous paid employment as measured by their wage residual decile while in paid employment. Our goal is to establish the answers to four questions. First, we ask whether the immigrant-native differences in entrepreneurship are explained by observable characteristics.

Second, we ask whether entrepreneurship in this sample is U-shaped in wage residuals, addressing hypotheses 1 and 2. Third, we ask whether immigrants are more likely than natives to be entrepreneurs along the entire range of the ability/wage-residual distribution, addressing hypotheses 3 and 4. Finally, we ask whether the relationship between ability and entrepreneurship is different for science and non-science entrepreneurship (addressing hypothesis 6) and whether the immigrant-native differences are similar in both sectors.

Most of our empirical work involves multinomial logit regressions of the likelihood of science or non-science entrepreneurship. These results are reported as odds ratios. Standard errors were clustered by person.

4.1. Is the immigrant entrepreneurship premium explained by observable characteristics of immigrants and natives?

Before examining the relationship of entrepreneurship and previous employment, we examine whether immigrants are more likely to become entrepreneurs than natives holding constant numerous observable human capital and demographic characteristics that are correlated with self-employment. Table 3 reports the odds ratios from a multinomial logit regression where the reference category is staying in paid employment in the subsequent period and the two alternative categories are becoming entrepreneurs in science and in non-science respectively in the subsequent period.[14] Being an immigrant increases the probability of becoming an entrepreneur in science relative to staying in paid employment. Controlling for calendar year, field of highest degree, race, age, gender, and marital status reduces immigrants' relative

[14] Here, we report the coefficients (as odds ratios) on the immigrant dummy only. Full regression results from this and all tables are available upon request.

advantage in science entrepreneurship.[15] In contrast, controlling for the level of highest education *increases* immigrants' relative advantage in science entrepreneurship; this is because immigrants are more likely to hold master's and doctorate degrees, which are negatively correlated with entrepreneurship (a finding consistent with previous results by Hunt 2011). After controlling for all of these observable characteristics, we find that the odds of an immigrant becoming a science entrepreneur relative to staying in paid employment is 1.45 times the odds for a native (column 5). This is consistent with immigrant having particularly large amounts of entrepreneurial abilities R.

However, being an immigrant has little to no effect on the probability of becoming an entrepreneur in non-science, relative to staying in paid employment. This may suggest that immigrants' entrepreneurial abilities – at least among this sample of the college educated – are limited to a particular type of entrepreneurship only.

4.2. Is the overall immigrant entrepreneurship premium explained by the distribution of immigrants and natives across wage residual deciles?

Next, we model the likelihood of a person presently in paid employment entering entrepreneurship (self-employed incorporated work) by the time of the subsequent survey, usually occurring two years later. The probability of entrepreneurship is modeled as a function of dummy variables for the person's wage residual decile in paid employment in addition to all covariates included in Table 3. This flexible specification of residual decile dummies allows us

[15] We do not feel that it would be appropriate to control for region, because the choice of region often follows from the decision to become an entrepreneur. It would be interesting to test whether the region of residence matters differently for immigrants and natives in entrepreneurship but our sample is too small to provide robust results.

to study whether nonlinearities and/or asymmetries exist in the relationship between wage residuals and self-employment.

Figure 1 displays the distribution of immigrant and native workers across the ten deciles of the wage residuals' distribution.[16] As can be seen in Figure 1, immigrants are disproportionately drawn from the 1st decile of the wage residuals' distribution relative to natives. As discussed in the introduction, this over-representation of immigrants at the bottom of the distribution could reflect differences in ability or language and communication skills. On the other hand, it could instead represent discrimination or under-estimation of skills, as we assumed in the development of Hypothesis 3.

Figure 2 divides immigrants by where they earned their highest degree. This figure demonstrates that only immigrants who did not earn their highest degrees in the US are more likely to be in the lowest decile of the wage residual distribution. In contrast, the wage residual distribution of immigrants who obtained their highest degrees in the US looks remarkably similar to those of natives. This evidence suggests that immigrants may be rewarded less in paid employment due to language or cultural differences, which is consistent with Hypothesis 3.

The mere fact that immigrants are more likely to be at the bottom of the wage residual distribution can contribute to an immigrant-native differential in entrepreneurship if entry into entrepreneurship is more common at the lower extreme of the ability distribution (as predicted by Hypotheses 1 and 3). If this hypothesis is correct, then we would expect the immigrant entrepreneurship premium to become smaller in magnitude when we control for the wage residual distribution in the regression. Understanding selection into entrepreneurship based on immigrants' ability is important from a policy perspective: if higher rates of entry into

[16] Note that although the wage equation was calculated based on natives only, the deciles were based on the predicted wages for both natives and immigrants. It is for this reason that the native distribution is not a flat line at 10%.

entrepreneurship by low-ability immigrants are what drives the immigrant premium in entrepreneurship, but innovation is created by those with high ability, then this would suggest that higher rates of immigration will not necessarily lead to more high-tech innovation.

In Table 4, we re-estimate the model with all controls from Columns 5 and 10 of Table 3, adding dummies for wage residual deciles, where the first decile is normalized to an odds ratio of 1. Since wage residuals are obtained from a wage equation, this estimation involves a two-step process. Therefore, we bootstrap the standard errors in the two-stage results. We report the coefficients (as odds ratios) on the dummies for the wage residual deciles as well as the immigrant dummy. Comparing Table 4 to Columns 5 and 10 of Table 3 indicates that incorporating wage residuals has very little impact on the immigrant premium in either science entrepreneurship or in non-science entrepreneurship. We conclude that the immigrant entrepreneurship premium is not due to the fact that immigrants are distributed differently than natives along the wage residual distribution.

4.3. Is there a different relationship between entrepreneurship and wage residuals in science and non-science?

The coefficients on the wage residual deciles from Table 4 display a clear J-shaped pattern for entry into *non-science* entrepreneurship as a function of wage residuals. Thus, workers whose wage residual is in any decile between the second and the ninth have a significantly lower probability of entering non-science entrepreneurship than workers who are in the very bottom of the residual distribution (first decile, normalized to 1) or in the top decile. What makes this a J-shaped relationship rather than a U-shaped one is that workers at the very top (10^{th} decile) have a much higher (in magnitude and significance) probability of entering non-science entrepreneurship than workers in the 1st decile. That is, both misfits and stars are overrepresented among non-science entrepreneurs, as predicted by Hypotheses 1 and 2. However, the rate of entry is higher among stars than misfits. This is similar to relationship between entrepreneurship and previous wage levels seen in Poschke 2013, Elfenbein *et al.* 2010, Braguinsky *et al.* 2012.

In contrast, for *science* entrepreneurship, there is no evidence of a J or U-shaped pattern in entrepreneurship as the wage residual increases. Instead, there is an increasing trend particularly starting in the 6th decile, with workers in the top three deciles significantly more likely to enter science entrepreneurship relative to those in the 1st decile. This is precisely the prediction of our model in Hypothesis 6.

4.4. Is the relationship between ability in paid employment and each type of entrepreneurship different for immigrants and natives?

In Table 4, we observed that immigrants are more likely to become science entrepreneurs than natives, even holding constant their position in the distribution of wage residuals and other observables. This raises the question of whether immigrants are uniformly more likely to become science entrepreneurs at all ability levels, or whether instead the immigrant premium is concentrated in certain parts of the wage residual distribution. Similarly, the zero effect of immigrant status on non-science entrepreneurship might obscure counteracting differences at different ability levels.

To investigate this, we estimate the model with two sets of residual decile dummies, one set for natives and the other for immigrants. Being a native in the first decile is the omitted category (and is thus normalized to 1). Table 5 contains the results of a multinomial logit regression in which the dependent variable captures the decision to enter science or non-science entrepreneurship in the next period and explanatory variables are the same controls as in Table 4 (and Column 5 of Table 3) plus these two sets of interaction terms of wage residual and immigrant status. Figures 3 and 4 plot the coefficients of the residual deciles terms for science and non-science entrepreneurship respectively.

As before, the patterns are quite different when we look at science and non-science entrepreneurship. In Figure 3, immigrants appear to have higher levels of science entrepreneurship at all deciles, as predicted by Hypothesis 4. We can reject the hypothesis that the odds ratios associated with the immigrant premium in science entrepreneurship are jointly 1[17] throughout the distribution (p-value<.001 in Table 5). Furthermore, both immigrants and natives have a pattern of increasing science entrepreneurship as wage residuals rise, as predicted by Hypothesis 6. However, the immigrant premium itself fluctuates a lot.

For non-science entrepreneurship, natives and immigrants each have a J-shaped relationship between non-science entrepreneurship and residual decile. Individuals who are at the bottom and top of the ability distribution are more likely to enter non-science entrepreneurship, with particularly high likelihoods at the top decile (consistent with Hypotheses 1 and 2). As illustrated in Figure 4, the two graphs for immigrants and natives almost overlap, and the p-value for the joint test that they are different at each decile is .67. We fail to reject the joint hypothesis that immigrants and natives have different likelihoods of entering non-science entrepreneurship at each decile of the wage-residual distribution. Therefore, the evidence in Figure 4 is not consistent with Hypothesis 4.

5. Mechanisms

[17] In other words, we reject the joint hypotheses that the immigrant and native coefficients equal each other at each decile.

In this section, we investigate some potential explanations for the immigrant premium in entrepreneurship, besides higher entrepreneurship abilities. These potential explanations are based on preferences and mismatch with employers in established firms.

5.1. Is immigrant entrepreneurship explained by preferences for self-employment?

One potential explanation for the immigrant premium in entrepreneurship is that immigrants may be more likely to prefer self-employment, holding constant other observable characteristics of the worker and job. The 1997 wave of SESTAT includes data about individuals' preferences for different working arrangements. Respondents were asked whether their preferred type of working arrangement was a permanent job, self-employment or some other type of working arrangement. In Table 6, we model the probability of entering entrepreneurship (in 1999) as a function of a dummy variable equal to 1 if the respondent preferred self-employment, as well as controls for education level, field, race, age, gender, and family structure in 1997. We first estimate the immigrant entrepreneurship premium on this smaller sample excluding the preference dummy but with other explanatory variables. We then add the preference variable in the final three columns. Hypothesis 5 predicted that the immigrants' advantage in entrepreneurship would disappear after controlling for preferences.

As expected, a stronger preference for self-employment is significantly and positively correlated with the probability that an individual is either a science or a non-science entrepreneur, although it explains a surprisingly small proportion of the variance in entrepreneurship. Of most interest to this paper, adding the preference for self-employment reduces the overall immigrant premium by only 9% (0.043 percentage points). The small size of this change is not surprising in light of the fact that there is no significant difference in the average preference for self-employment of natives (29.5% prefer) and immigrants (30.5% prefer.) Preferences affect science and non-science entrepreneurship equally. This is inconsistent with Hypothesis 5, and further suggests that something other than preferences, educational attainment, field, or family structure is responsible for the fact that immigrants are more likely than natives to be science entrepreneurs. This is particularly true for science entrepreneurship.[18]

The fact that neither ability as measured with wage residuals nor a taste for self-employment fully explain the immigrant entrepreneurship premium suggests the necessity of carefully considering the aforementioned alertness or information-based theories of entrepreneurship.[19] Future research should seek more fine-grained data on the specific natures of entrepreneurial ventures to further examine the role of alertness and information in immigrant entrepreneurship.[20]

5.2. Is the immigrant entrepreneurship premium greater for those immigrants who earned their highest degree abroad?

A second alternative would be to estimate the model treating those immigrants with their highest degree in the US separately from those with their highest degree abroad. Returns to foreign degrees may be lower than returns to US degrees either because the former may send noisier signals to employers or because the quality of education abroad is lower. Thus immigrants who obtained their degrees abroad may be disadvantaged in paid employment

[18] Immigrants also have a significantly higher tendency than natives to be non-science entrepreneurs, controlling for preferences, whereas they had similar tendencies when preferences were not controlled for (Table 3 column 10) for the whole sample; further analysis (not shown) indicates that the 1997 subset was somewhat different than the entire sample on this point.

[19] Empirical research on alertness is scarce as alertness is difficult to measure. One exception is Tang et al. (2012), who developed an alertness scale based on 13 items. They show that alertness is positively correlated with "prior knowledge" (Shane 2000).

[20] Progress in this direction has recently been made by Kerr and Mandorff (2016) who examine the concentration of different ethnic groups in specific sectors.

relative to natives and immigrants who obtained their degrees in the US. In Table 7, we test whether immigrants who obtained their highest degrees in the US and immigrants who obtained their highest degree abroad are different in their rates of either science or non-science entrepreneurship.

After controlling for field, education, demographics, and year (but not wage residuals), we find that those with a highest degree from an institution in the US have an odds ratio of entering science entrepreneurship of 1.29, whereas those with a highest degree from an institution outside the US have an odds ratio of 1.69, and the difference between these odds ratios is statistically significant (p-value<.01). Controlling for wage residuals barely changes the odds ratio for those who obtained their highest degree in the US and only slightly and insignificantly increases the odds ratio for those who obtained a highest degree abroad, to 1.75. We conclude that the science immigrant premium is particularly strong for those who were not educated in the US, and that these immigrants are 75% more likely than natives to enter science entrepreneurship. Differently from the prediction of Hypothesis 3, the fact that immigrants who obtained their higher education abroad are overrepresented at the bottom of the wage residual distribution does not explain their advantage in science entrepreneurship. As in previous tables, the immigrant premia are smaller in non-science entrepreneurship and indistinguishable from zero; this applies both to those with highest degrees from the US and those without. Controlling for wage residuals has no significant effect on this conclusion.

We are also interested in knowing whether the relationship between ability and entrepreneurship is different for immigrants who obtained their highest degree in the US and those who obtained their highest degree abroad. One might expect entrepreneurial alertness to matter differently for individuals from different backgrounds. To investigate this, we estimate the model with three sets of wage-residual decile dummies, one set for natives, one for immigrants who obtained their highest degree in US and one for immigrants who obtained their highest degree abroad. Figure 5 plots the coefficients of the residual-decile odds-ratios for these three groups for science entrepreneurship only; as before, natives in the first decile are normalized to 1. Natives are the least likely to enter science entrepreneurship at all residual deciles and have a clear upwardly sloping pattern. Immigrants' patterns are noisier because of smaller samples. Immigrants who earned their highest degrees from US institutions also display an increasing trend and a relatively small and noisy science immigrant premium. Intriguingly, it appears that the immigrant premium in science entrepreneurship comes largely from those with their highest degrees from institutions outside the US, especially in the lower-middle part of the wage residual distribution. One should be cautious about over-interpreting these differences due to the relatively small number of entrepreneurs in each decile. However, the higher rates of science entrepreneurship among immigrants with non-US highest degrees may be consistent with higher levels of resourcefulness due to the unique perspective conferred by their cultural and educational experiences outside the US.

Figure 6 plots the differences in non-science between the two different groups of immigrants relative to natives at each residual decile. All three groups have J-shaped patterns and there are no clear differences in immigrant premium between the two groups of immigrants: there are only a few statistically significant differences at any decile between different groups, and the sign of the differences change.

5.3. Is the immigrant entrepreneurship greater for those immigrants whose native tongue is not English or whose culture is quite dissimilar to the US?

We test whether immigrants who come from non-English countries or countries that are culturally distant from the United States are more likely to become entrepreneurs. Mismatch with employers may be more likely for these groups due to difficulties in communication and/or lack of cultural integration. We classify countries as English speaking and non-English speaking using the definition proposed by Bleakley and Chin (2004). We classify countries from Europe and Commonwealth countries as “culturally similar” to the United States; we classify all other countries as “culturally dissimilar”.

As shown in Table 8, immigrants from non-English speaking countries have a higher probability of entering entrepreneurship than immigrants from English-speaking countries – both in science (p-value=.11) and in non-science entrepreneurship (p-value=.01). Interestingly, sign of the immigrants-native gap differs for these two immigrant groups, but in different ways in science and non-science entrepreneurship. Natives have a (significantly) lower likelihood than immigrants from non-English-speaking countries to enter science entrepreneurship (55%) but a significantly higher likelihood than immigrants from English- speaking countries to enter non-science entrepreneurship (29%). These results hold when controlling for the distribution of wage residuals in paid employment, leading to different conclusions than those predicted by Hypothesis 3.

Table 9 shows that entrepreneurship by immigrants from culturally similar v. dissimilar countries shows exactly the same patterns as entrepreneurship by immigrants from English-speaking and non-English speaking countries: immigrants from culturally dissimilar countries are more likely to enter entrepreneurship than those from culturally-similar countries; and immigrants from culturally dissimilar countries are more likely than natives to become entrepreneurs in science while those from culturally similar countries are less likely than natives to become entrepreneurs in non-science. Again, controlling for wage residuals' deciles does not affect these results.

6. Robustness Checks: entrepreneurship and wages

Since so much of the previous literature on entrepreneurship and ability is based on wages rather than wage residuals, we have also re-estimated the relationship between entrepreneurship and ability with the coefficients on immigrants' and natives' wage deciles given in Table 10 and graphed in Figures 7 and 8. The patterns are very similar to those in Table 5, Figures 3 and 4 respectively.

7. Conclusion

We use data from a large longitudinal survey of US-based scientists to study how ability in paid employment affects science and non-science entrepreneurship for immigrants and natives. Individuals at the extremes of the ability distribution – sometimes referred to in the literature as "misfits" and "stars" – have been shown to be more likely to become entrepreneurs. The literature has also uncovered an "immigrant premium" in entrepreneurship. We ask whether the immigrant entrepreneurship premium is explained by the greater tendency of immigrants to be located at the extremes of the ability distribution.

We show that a large share of immigrants with scientific human capital are underpaid relative to their observable characteristics (as measured by negative wage residuals). We think of these individuals as having a low opportunity costs of entering entrepreneurship, which is consistent with the fact that we observe higher rates of entrepreneurship among individuals with the lowest wage residuals. However, immigrants and natives with similar wage residuals enter non-science entrepreneurship at similar rates: we do not find evidence that low opportunity costs cause immigrants to become non-science entrepreneurs.

Results are quite different for science entrepreneurship, where we estimate a large and robust immigrant premium across the distribution of wage residuals. This premium is not explained by stronger preferences for entrepreneurship among immigrants, as measured by survey responses. Instead, it seems consistent with immigrants' having larger endowments of entrepreneurial skills or greater alertness to entrepreneurial opportunities. Intriguingly, however, the immigrant premium is largest for non-US degree holders toward the bottom of the wage residual distribution (those who are somewhat underpaid relative to their characteristics). This suggests that, in science entrepreneurship, there may also be a role for entrepreneurship driven by lower opportunity costs.

The findings from this paper have implications for immigration policy. We start from the position that scientific endeavors in general, and science entrepreneurship in particular, are important for this country's long-run economic growth. Immigrants to the US are more likely to have studied science and engineering than natives. We show that, after controlling for educational field and level, immigrants are substantially more likely to enter science entrepreneurship compared to natives. This result is consistent with previous findings by Hunt (2011), who used a different and more general definition of entrepreneurship (not focused on science) and a cross-sectional sample of BAs from all fields. However, the current paper adds to this literature by showing that even after controlling for the distribution of wage residuals in paid employment, the foreign-born are significantly more likely than natives to start a science-based business.

The science entrepreneurship immigrant premium is greatest for those immigrants who receive their highest degree outside the US, who come from non-English speaking countries and who come from countries that are culturally distant from the United States. This finding suggests the possibility that many immigrants start businesses because they are under-rewarded in established firms. Further research is warranted to investigate this possibility more definitively. From a policy perspective, this result suggests that the programs that focus on the immigration of individuals with a bachelor's degree or higher in science may lead to higher rates of business formation in science relative to programs that focus on the immigration of foreign students.

References

Anderson, S. and Platzer, M. (2006). *American Made: The Impact of Immigrant Entrepreneurs and Professionals on U.S. Competitiveness*. National Venture Capital Association.

Astebro, T., Chen, J., and Thompson, P. (2011). “Stars and misfits: Self-employment and labor market frictions.” *Management Science* 57(11), 1999-2017.

Astebro, T. and Thompson, P. (2011): “Entrepreneurs: Jacks of all trades or hobos?” *Research Policy* 40(5), 637-649.

Bleakly, H. and Chin, A. (2004) “Language Skills and Earnings: Evidence from Childhood Immigrants.” *Review of Economics and Statistics* 86(2), 481-496.

Borjas, G.S (1986) “The self-employment experience of immigrants.” *Journal of Human Resources* 21(4), 485-506.

Borjas, G.J. and Bronars, S.G. (1989), “Consumer Discrimination and Self-Employment”, *Journal of Political Economy* 97 (3), 581-605.

Braguinsky, S., Klepper, S, and Ohyama, S. (2012) "High-tech entrepreneurship." J*ournal of Law and Economics* 55 (4), 869-900.

Carnahan, S., Agarwal, R. and Campbell, B.A. (2012) "Heterogeneity in turnover: The effect of relative compensation dispersion of firms on the mobility and entrepreneurship of extreme performers." *Strategic Management Journal* 33 (12). 1411-1430.

Chung, W. and A. Kalnins (2006) “Social capital, geography, and Survival: Gujarati immigrant entrepreneurs in the U.S. lodging industry,” *Management Science* 52(2): 233-247

D’este, P., & Perkmann, M. (2011). Why do academics engage with industry? The entrepreneurial university and individual motivations. *The Journal of Technology Transfer*, 36(3), 316-339.

Elfenbein, D.W., Hamilton, B.H. and Zenger, T.R. (2010). “The Small Firm Effect and the Entrepreneurial Spawning of Scientists and Engineers.” *Management Science* 56(4), 659-681.

Fairlie, R. (2008). *Estimating the Contribution of Immigrant Business Owners to the U.S. Economy*. U.S. Small Business Administration Report (November)

Fairlie, R. and Lofstrom, M. (2014). “Immigration and Entrepreneurship.” in Chiswick, B. and Miller, P.W. *Handbook of the Economics of International Migration* Vol.1B Chapter 17. Amsterdam: North Holland.

Ferrer, A. and Riddell, W. C. (2008) “Education, credentials, and immigrant earnings.” *Canadian Journal of Economics* 41(1), 186-216.

Gort, M. and Lee, S.H. (2007) “The Rewards to Entrepreneurship.” Working paper, SUNY Buffalo. Available at papers.ssrn.com.

Hamilton, B.H. (2000), “Does Entrepreneurship Pay? An Empirical Analysis of the Returns to Self-Employment.” *Journal of Political Economy* 108(3), 604-631.

Hart, D.M. and Acs, Z. J. (2011). “High-Tech Immigrant Entrepreneurship in the United States.” *Economic Development Quarterly* (May) 25 (2), pp. 116-29.

Hayek, F.A. (1945) “The Use of Knowledge in Society,” *American Economic Review* 25(4): 519-530.

Hipple, S. (2004), “Self-Employment in the United States: an update.” *Monthly Labor Review* 127(7), 13-23.

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

Hunt, J. (2011). “Which Immigrants Are Most Innovative and Entrepreneurial? Distinctions by Entry Visa.” *Journal of Labor Economics*, 29(3), 417-457.

Jovanovic, B. (1994) “Firm Formation with Heterogeneous Management and Labor Skills.” *Small Business Economics*, 6: 185-191.

Kerr, S. P., & Kerr, W. R. (2015). Immigrant entrepreneurship. In *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*. University of Chicago Press.

Kerr, W.R. (2013) “U.S. High-Skilled Immigration, Innovation, and Entrepreneurship: Empirical Approaches and Evidence.” *NBER Working Paper* No. 19377.

Kerr, W.R. and Mandorff, M. (2016) “Social Networks, Ethnicity, and Entrepreneurship” *Harvard Business School Working Paper 16 – 042.*

Kirzner, I. (1972) *Competition and Entrepreneurship,* Chicago: University of Chicago Press.

Kirzner, I. (1979) *Perception, Opportunity and Profit; Studies in the Theory of Entrepreneurship*, Chicago: University of Chicago Press.

Kirzner, I. (1999) “Creativity and/or Alertness: A Reconsideration of the Schumpeterian Entrepreneur,” *Review of Austrian Economics* 11: 5-17.

Lazear, E. P. (2004). “Balanced Skills and Entrepreneurship.” *American Economic Review* 94(2): 208-211.

Lazear, E. P. (2005). “Entrepreneurship”. *Journal of Labor Economics*, 23(4), 649-680.

Moller, K. (2010). Sense-making and agenda construction in emerging business networks—How to direct radical innovation. *Industrial Marketing Management*, 39(3), 361-371.

Murray, F. (2004). The role of academic inventors in entrepreneurial firms: sharing the laboratory life. *Research Policy*, 33(4), 643-659.

Murphy, K.M.; Shleifer, A., Vishny, R.W. (1991) "The Allocation of Talent: Implications for Growth." *Quarterly Journal of Economics*, 106(2), 503-30.

Nathan, M. (2014). "The wider economic impacts of high-skilled migrants: a survey of the literature for receiving countries." *IZA Journal of Migration* 3(4), pages 1-20.

Ohyama, A. (2007) "Entrepreneurship and Advanced Technical Knowledge." Working Paper, Ewing Marion Kauffman Foundation. Available at http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.362.7099&rep=rep1&type=pdf

Poschke, M. (2013), Who becomes an entrepreneur? Labor market prospects and occupational choice."*Journal of Economic Dynamics and Control*, 37(3), 693-710.

Rider, C. I., Thompson, P., Kacperczyk, A., and Tåg, J.(2013). "Experience and Entrepreneurship." Research Institute of Industrial Economics Working Paper No.970. Available at http://www.ifn.se/wfiles/wp/wp970.pdf.

Roach, M., & Sauermann, H. (2015). Founder or joiner? The role of preferences and context in shaping different entrepreneurial interests. *Management Science*, 61(9), 2160-2184.

Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford economic papers*, 3(2), 135-146.

Shane, Scott (2000), "Prior Knowledge and the Discovery of Entrepreneurial Opportunities" *Organization Science*, Vol. 11, No. 4, August 2000, pp. 448-469.

Stuart, T. E., & Ding, W. W. (2006). When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences1. *American Journal of Sociology*, 112(1), 97-144.

Tang, J., Kacmar, K. M. M., & Busenitz, L. (2012). Entrepreneurial alertness in the pursuit of new opportunities. *Journal of Business Venturing*, 27(1), 77-94.

Venkataraman, S. (1997). The distinctive domain of entrepreneurship research. *Advances in entrepreneurship, firm emergence and growth*, 3(1), 119-138.

Wadhwa, V., Rissing, B. Saxenian, A.L. and Gereffi, G. (2007). *Education, Entrepreneurship and Immigration: America's New Immigrant Entrepreneurs, Part II.* (June 11).

Zucker, L. G., Darby, M. R., & Brewer, M. B. (1998). Intellectual human capital and the birth of US biotechnology enterprises. *The American Economic Review*, 88(1), 290.

Zucker, L. G., Darby, M. R., & Armstrong, J. S. (2002). Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. *Management Science*, 48(1), 138-153.

Table 1 Self-Employment and Entrepreneurship

Entrepreneurship and Not incorporated Self-employment				
Percent of natives/immigrants who are:	Self-employed incorporated (Entrepreneurs)		Self-employed not incorporated	
	Natives	Immigrants	Natives	Immigrants
	8.93	11.07	4.80	4.52
t-statistic of difference	20.13***		-3.56***	
Science Entrepreneurship and Not incorporated Science Self-employment				
Percent of natives/immigrants who are:	Self-employed incorporated (Entrepreneurs) in science		Self-employed not incorporated in science	
	Natives	Immigrants	Natives	Immigrants
	2.08	4.14	0.69	0.92
t-statistic of difference	36.68***		7.39***	
Non-science Entrepreneurship and Not Incorporated Non-science Self-employment				
Percent of natives/immigrants who are:	Self-employed incorporated (Entrepreneurs) in non-science		Self-employed not incorporated in non-science	
	Natives	Immigrants	Natives	Immigrants
	6.85	6.85	4.12	3.61
t-statistic of difference	0.85		-7.03***	
Number of observations	422,571	116,994	422,571	116,994

Notes: Data from 1993-2010 SESTAT. Only full-time workers are included in the sample. Immigrants are defined as individuals who were born outside the United States and did not migrate during their childhood. Summary statistics obtained using survey weights.
Note that for each immigrant group, adding the science and non-science entrepreneurship incidence yields the total entrepreneurship incidence, and similarly for non-incorporated self-employment.

Table 2 Entrepreneurship (self-employed incorporated) in the subsequent period for those in paid employment

Percent of natives/immigrants who are:	**Entrepreneurs**	
	Natives	Immigrants
	4.03	4.57
t-statistic of difference	13.85***	
Percent of natives/immigrants who are:	**Entrepreneurs in science**	
	Natives	Immigrants
	1.18	2.67
t-statistic of difference	25.60***	
Panel C: Non-science		
Percent of natives/immigrants who are:	**Entrepreneurs in non-science**	
	Natives	Immigrants
	2.85	2.75
t-statistic of difference	-1.32	
Number of observations	246,405	64,459

Notes: Data from 1993, 1995, 1997, 2003, 2006, 2008 and 2010 SESTAT. Only full-time workers who are observed at least twice and are observed in paid employment at least once are included in the sample. Immigrants are defined as individuals who were born outside the United States and did not migrate during their childhood. Summary statistics obtained using survey weights.

Table 3: Probability of entrepreneurship in the next period, by type of entrepreneurship

Multinomial logit	Probability of science entrepreneurship					Probability of non-science entrepreneurship				
Base category: paid employment										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	2.3093***	2.0752***	2.2133***	1.7226***	1.4522***	0.9759	0.9056*	0.9490	1.0324	1.0253
	(0.1278)	(0.1171)	(0.1270)	(0.1023)	(0.1169)	(0.0552)	(0.0522)	(0.0564)	(0.0626)	(0.0782)
Master			0.0.9568	0.9491	0.9330			0.6436***	0.5174***	0.5020***
			(0.0592)	(0.0634)	(0.0627)			(0.0406)	(0.0369)	(0.0360)
Ph.D.			0.3984***	0.4163***	0.3913***			0.2613***	0.2560***	0.2200***
			(0.0316)	(0.0350)	(0.0335)			(0.0325)	(0.0333)	(0.0289)
Professional Degrees			0.6006***	1.3095	1.1313			3.2436***	3.2560***	2.6629***
			(0.1132)	(0.2958)	(0.2578)			(0.2290)	(0.3270)	(0.2756)
Calendar year dummies	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Field of highest degree dummies	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Age (entered as a cubic)	No	No	No	No	Yes	No	No	No	No	Yes
Demographic characteristics	No	No	No	No	Yes	No	No	No	No	Yes
Observations	310,864	310,864	310,864	310,864	310,864	310,864	310,864	310,864	310,864	310,864
Adjusted R square	0.0043	0.0377	0.0540	0.0793	0.0852	0.0039	0.0301	0.0674	0.0891	0.0935

Notes: From multinomial logit regression. Coefficients reported as odds ratios relative to paid employment. Standard errors in parenthesis are robust to clustering at the individual level. *** statistically significant at the 1% level; ** statistically significant at the 5% level; * statistically significant at the 10% level. Demographic characteristics include race, gender, gender-specific marital status and children dummy, and whether the spouse works. For each specification, probability of science entrepreneurship and probability of non-science entrepreneurship are estimated using the same regression. For instance, estimates in Columns 1 and 6 are obtained from the same regression.

Table 4: Entrepreneurship in the next period and wage residuals in paid employment

Multinomial logit regression. Base category: paid employment	Science entrepreneurship	Non-science entrepreneurship
	(1)	(2)
Immigrant	1.4723***	0.9903
	(0.1130)	(0.0797)
residual decile=2	0.9654	0.6568***
	(0.1485)	(0.0734)
residual decile=3	1.2766	0.5816***
	(0.1761)	(0.0629)
residual decile=4	1.1112	0.4511***
	(0.1768)	(0.0586)
residual decile=5	1.2479	0.5992***
	(0.1769)	(0.0726)
residual decile=6	1.1549	0.5214***
	(0.1601)	(0.0632)
residual decile=7	1.2246	0.5728***
	(0.1829)	(0.0643)
residual decile=8	1.3051*	0.6389***
	(0.1720)	(0.0746)
residual decile=9	1.4461**	0.8515*
	(0.1980)	(0.0848)
residual decile=10	1.3916*	1.3523***
	(0.2013)	(0.1286)
Observations	310,864	
Adjusted R square	0.103	

Notes: Estimation using multinomial logit. Coefficients reported as odds ratios with paid employment as base. Bootstrapped standard errors in parenthesis are robust to clustering at the individual level. *** statistically significant at the 1% level; ** statistically significant at the 5% level; * statistically significant at the 10% level. Regressions control for all control variables from Column 5 of Table 3. Estimates in Columns 1 and 2 are obtained from the same regression.

Table 5: Entrepreneurship in the next period and wage residuals for natives & immigrant

Multinomial logit regression Base category: paid employment	Science entrepreneurship	Non-science entrepreneurship
	(1)	(2)
resid. decile=2*native	0.8633	0.6594***
	(0.1818)	(0.0853)
resid. decile=3*native	1.1912	0.5936***
	(0.2410)	(0.0733)
resid. decile=4*native	1.0364	0.4267***
	(0.2107)	(0.0633)
resid. decile=5*native	1.1304	0.6140***
	(0.2109)	(0.0777)
resid. decile=6*native	1.1479	0.5012***
	(0.2329)	(0.0716)
resid. decile=7*native	1.2245	0.5685***
	(0.2481)	(0.0764)
resid. decile=8*native	1.3060	0.6277***
	(0.2643)	(0.0825)
resid. decile=9*native	1.3775*	0.8561
	(0.2656)	(0.1034)
resid. decile=10*native	1.3913*	1.3666***
	(0.2942)	(0.1314)
resid. decile=1*immigrant	1.3461	0.9856
	(0.2992)	(0.1554)
resid. decile=2*immigrant	1.5966	0.6286**
	(0.3738)	(0.1177)
resid. decile=3*immigrant	1.9432*	0.5020***
	(0.4460)	(0.1087)
resid. decile=4*immigrant	1.7211*	0.6100**
	(0.4280)	(0.1263)
resid. decile=5*immigrant	2.0313**	0.4949***
	(0.4551)	(0.1250)
resid. decile=6*immigrant	1.5118	0.6453**
	(0.3537)	(0.1245)
resid. decile=7*immigrant	1.5652	0.5911***
	(0.3556)	(0.1260)
resid. decile=8*immigrant	1.6489*	0.7040**
	(0.3656)	(0.1497)
resid. decile=9*immigrant	2.1110**	0.8029
	(0.4664)	(0.1596)
resid. decile=10*immigrant	1.7182*	1.2309
	(0.4126)	(0.1770)
Observations	310,864	
Adjusted R square	0.0935	

Notes: Coefficients reported as odds ratio. See notes Table 4. Estimates in Columns 1 and 2 are obtained from the same regression

Table 6: Entrepreneurship and Preferences for Self-Employment

	All entrepreneurship		Science entrepreneurship	Non-science entrepreneurship
	(1)	(2)	(3)	(4)
Immigrant	1.464***	1.421***	1.564***	1.343***
	(0.124)	(0.125)	(0.269)	(0.132)
Prefer self-employment		9.753***	9.337***	9.805***
		(0.824)	(1.586)	(0.935)
Observations	46,213	46,213	46,215	
Pseudo R-square	0.0749	0.188	0.190	

Notes: Coefficients reported as odds ratio. See notes Table 4. Estimates in Columns 3 and 4 are obtained from the same regression.

Table 7: Entrepreneurship in the next period and immigrants with a highest degree abroad

Multinomial logit Base category: paid employment	Science Entrepreneurship	Non-science Entrepreneurship	Science Entrepreneurship	Non-science Entrepreneurship
	(1)	(2)	(3)	(4)
Immigrant* Highest degree abroad	1.6867***	1.0721	1.7487***	1.0126
	(0.1666)	(0.1057)	(0.1747)	(0.1001)
Immigrant* Highest degree US	1.2883***	0.9888	1.2886***	0.9731
	(0.1158)	(0.0877)	(0.1158)	(0.0865)
residual decile=2			0.9910	0.6581***
			(0.1462)	(0.0742)
residual decile=3			1.3156*	0.5829***
			(0.1888)	(0.0668)
residual decile=4			1.1461	0.4521***
			(0.1613)	(0.0522)
residual decile=5			1.2869*	0.6006***
			(0.1838)	(0.0697)
residual decile=6			1.1922	0.5227***
			(0.1682)	(0.0612)
residual decile=7			1.2652*	0.5741***
			(0.1777)	(0.0657)
residual decile=8			1.3530**	0.6406***
			(0.1871)	(0.0721)
residual decile=9			1.4933***	0.8537
			(0.2060)	(0.0898)
residual decile=10			1.4361**	1.3559***
			(0.2065)	(0.1248)
Observations	310,864	310,864	310,864	310,864
Adjusted R square	0.0853	0.0853	0.0934	0.0934

Notes: Coefficients reported as odds ratio. See notes Table 4. Estimates in Columns 1 and 2 are obtained from the same regression. Estimates in Columns 3 and 4 are obtained from the same regression.

Table 8: Entrepreneurship in the next period and immigrants from non-English speaking countries

Multinomial logit Base category: paid employment	Science Entrepreneurship	Non-science Entrepreneurship	Science Entrepreneurship	Non-science Entrepreneurship
	(1)	(2)	(3)	(4)
Immigrant * English Speaking Country	1.1208	0.7131**	1.1139	0.6740***
	(0.2160)	(0.1157)	(0.2026)	(0.1090)
Immigrant * Non-English Speaking Country	1.5460***	1.1182	1.5768***	1.0872
	(0.1331)	(0.0953)	(0.1289)	(0.0995)
residual decile=2			0.9713	0.6607***
			(0.1491)	(0.0738)
residual decile=3			1.2818*	0.5838***
			(0.1764)	(0.0632)
residual decile=4			1.1193	0.4541***
			(0.1779)	(0.0590)
residual decile=5			1.2550	0.6025***
			(0.1781)	(0.0730)
residual decile=6			1.1623	0.5251***
			(0.1607)	(0.0638)
residual decile=7			1.2342	0.5776***
			(0.1839)	(0.0648)
residual decile=8			1.3134*	0.6436***
			(0.1728)	(0.0752)
residual decile=9			1.4584**	0.8593*
			(0.1996)	(0.0860)
residual decile=10			1.4049**	1.3657***
			(0.2027)	(0.1300)
Observations	310,176	310,176	310,176	310,176
Adjusted R square	0.0854	0.0854	0.0934	0.0934

Notes: Coefficients reported as odds ratio. See notes Table 4. Estimates in Columns 1 and 2 are obtained from the same regression. Estimates in Columns 3 and 4 are obtained from the same regression.

Table 9: Entrepreneurship in the next period and immigrants from culturally dissimilar countries

Multinomial logit Base category: paid employment	Science Entrepreneurship	Non-science Entrepreneurship	Science Entrepreneurship	Non-science Entrepreneurship
	(1)	(2)	(3)	(4)
Immigrant * Culturally Similar	1.1803	0.7069**	1.1612	0.6694***
	(0.1903)	(0.0999)	(0.1799)	(0.0880)
Immigrant * Culturally Dissimilar	1.5553***	1.1543	1.5954***	1.1235
	(0.1401)	(0.1042)	(0.1373)	(0.1086)
Residual decile = 2			0.9680	0.6608***
			(0.1488)	(0.0739)
Residual decile = 3			1.2806	0.5844***
			(0.1766)	(0.0634)
Residual decile = 4			1.1182	0.4546***
			(0.1777)	(0.0591)
Residual decile = 5			1.2551	0.6034***
			(0.1781)	(0.0731)
Residual decile = 6			1.1620	0.5259***
			(0.1606)	(0.0639)
Residual decile = 7			1.2331	0.5782***
			(0.1836)	(0.0649)
Residual decile = 8			1.3136**	0.6452***
			(0.1730)	(0.0754)
Residual decile = 9			1.4607**	0.8614
			(0.2001)	(0.0860)
Residual decile = 10			1.4073**	1.3685***
			(0.2035)	(0.1304)
Observations	310,176	310,176	310,176	310,176
Adjusted R square	0.0855	0.0855	0.0935	0.0935

Notes: Coefficients reported as odds ratio. See notes Table 4. Estimates in Columns 1 and 2 are obtained from the same regression. Estimates in Columns 3 and 4 are obtained from the same regression.

Table 10: Entrepreneurship in the next period and immigrants and wage deciles

Multinomial logit Base category: paid employment	Science Entrepreneurship	Non-science Entrepreneurship
	(1)	(2)
wage decile=2*native	0.7435	0.8019*
	(0.1819)	(0.1035)
wage decile=3*native	0.8654	0.6744***
	(0.2040)	(0.0935)
wage decile=4*native	1.1678	0.4473***
	(0.2677)	(0.0637)
wage decile=5*native	1.1580	0.4381***
	(0.2635)	(0.0649)
wage decile=6*native	1.1747	0.5507***
	(0.2602)	(0.0807)
wage decile=7*native	1.3719	0.6363***
	(0.2991)	(0.0887)
wage decile=8*native	1.1887	0.6881**
	(0.2646)	(0.1019)
wage decile=9*native	1.2572	0.7995
	(0.2800)	(0.1171)
wage decile=10*native	1.3928	1.4757***
	(0.3163)	(0.1992)
wage decile=1*immigrant	1.3177	1.0702
	(0.4192)	(0.2173)
wage decile=2*immigrant	1.3036	0.9080
	(0.3969)	(0.1941)
wage decile=3*immigrant	1.8439**	0.5918**
	(0.5357)	(0.1342)
wage decile=4*immigrant	1.4784	0.6787*
	(0.3914)	(0.1438)
wage decile=5*immigrant	1.4289	0.5112***
	(0.3831)	(0.1121)
wage decile=6*immigrant	2.0055***	0.4682***
	(0.4947)	(0.1082)
wage decile=7*immigrant	1.8136**	0.5173***
	(0.4526)	(0.1198)
wage decile=8*immigrant	2.0059***	0.6124**
	(0.4736)	(0.1218)
wage decile=9*immigrant	2.0926***	0.7294
	(0.4938)	(0.1443)
wage decile=10*immigrant	1.4985	1.4511**
	(0.3694)	(0.2348)
Observations	310,864	
Adjusted R squared	0.0983	

Notes: Estimation using multinomial logit. Coefficients reported as odds ratios with paid employment as base. Standard errors in parenthesis are robust to clustering at the individual level. *** statistically significant at the 1% level; ** statistically significant at the 5% level; * statistically significant at the 10% level. Regressions control for all control variables from Column 5 of Table 3. Estimates in Columns 1 and 2 are obtained from the same regression.

Figure 1 Distribution of Immigrants and Natives across deciles of wage residuals

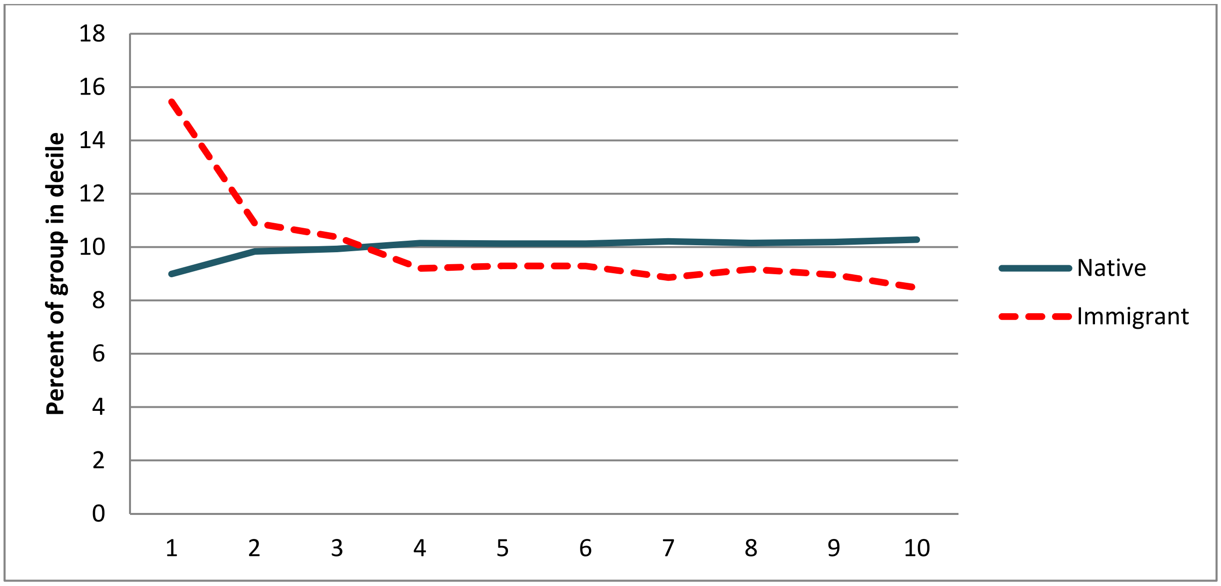


Figure 2 Distribution of Immigrants and Natives across deciles of wage residuals, by location of highest degree

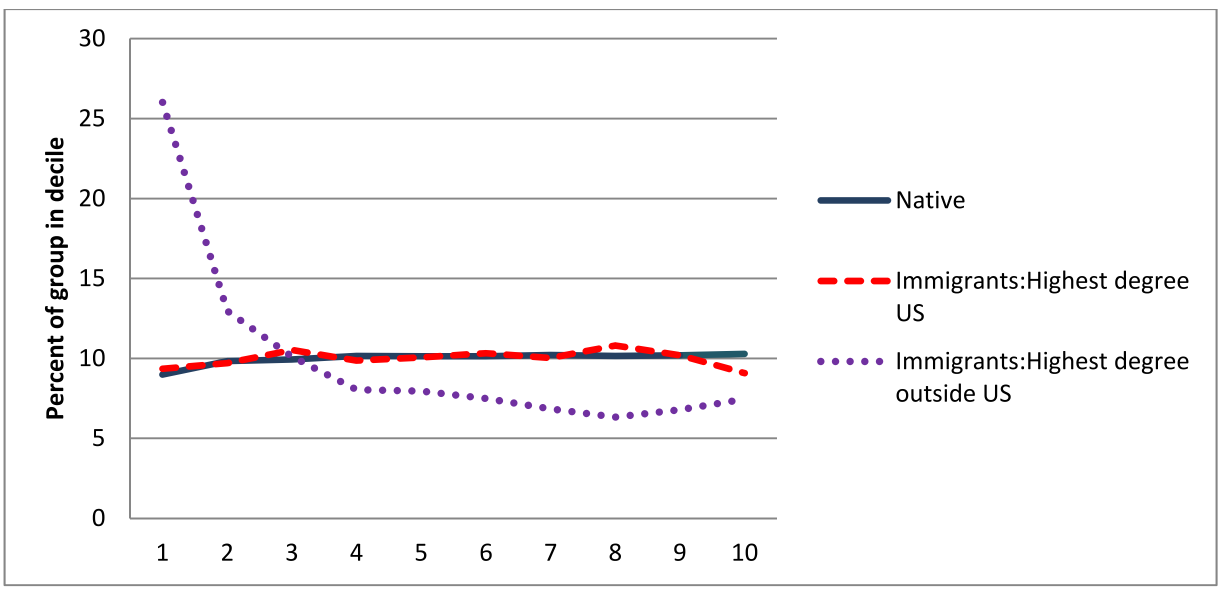
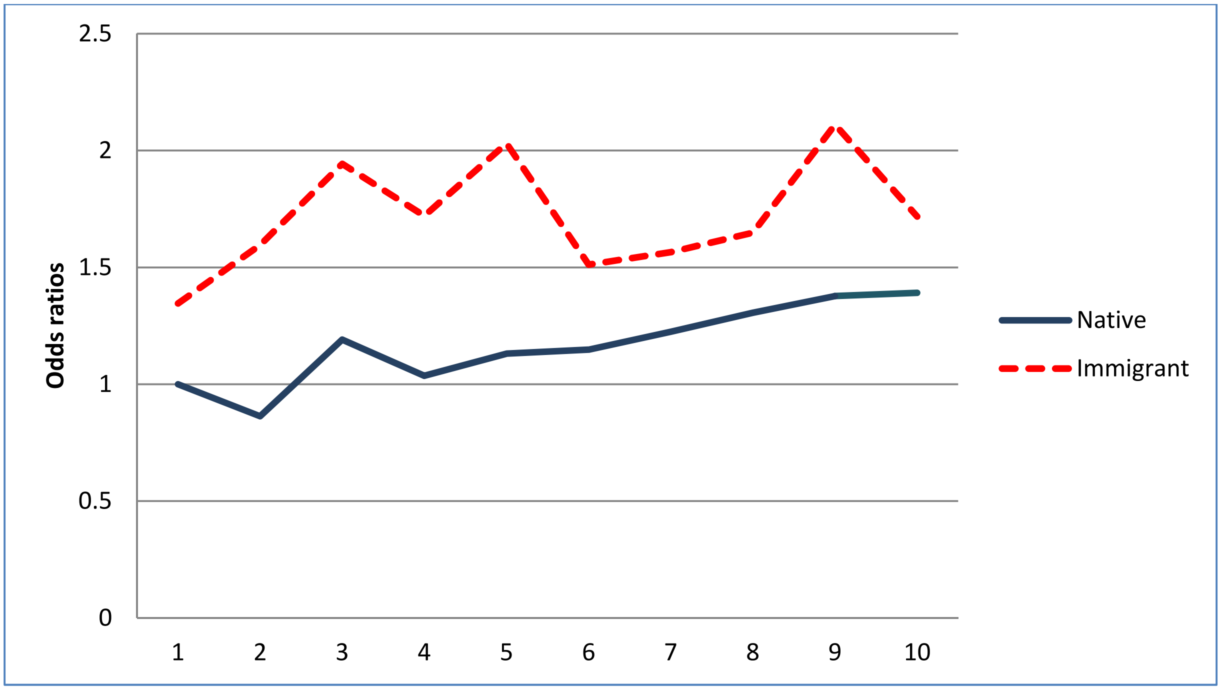
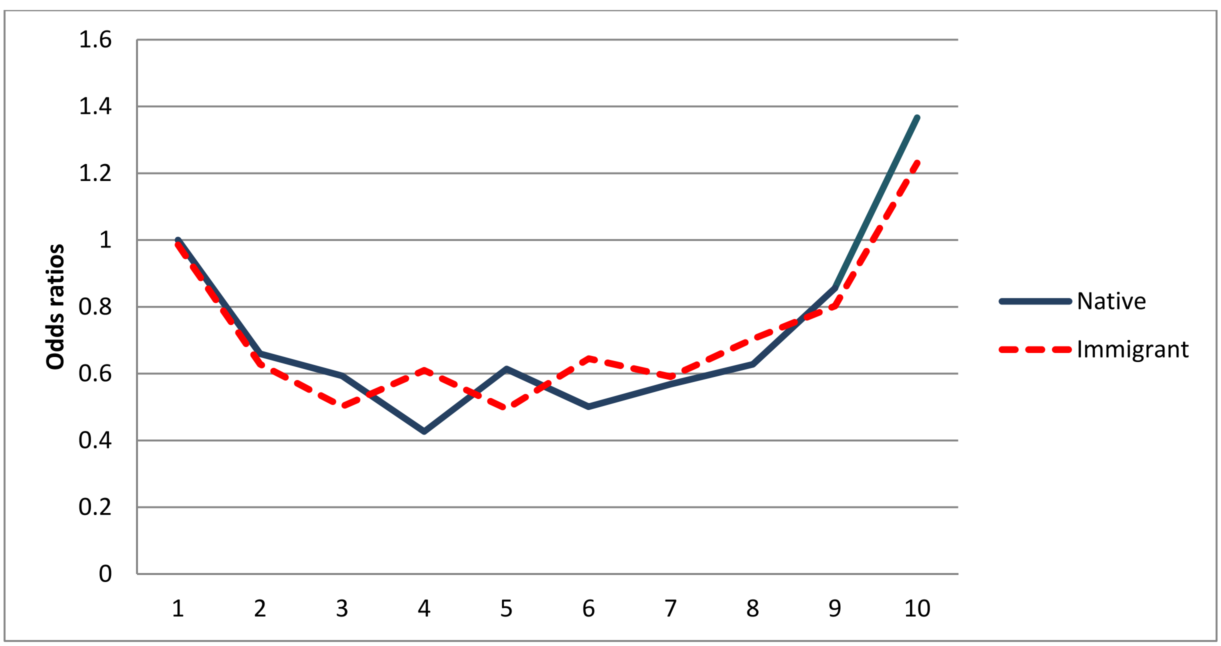


Figure 3 Science Entrepreneurship in the Next Period and Deciles of Wage Residuals



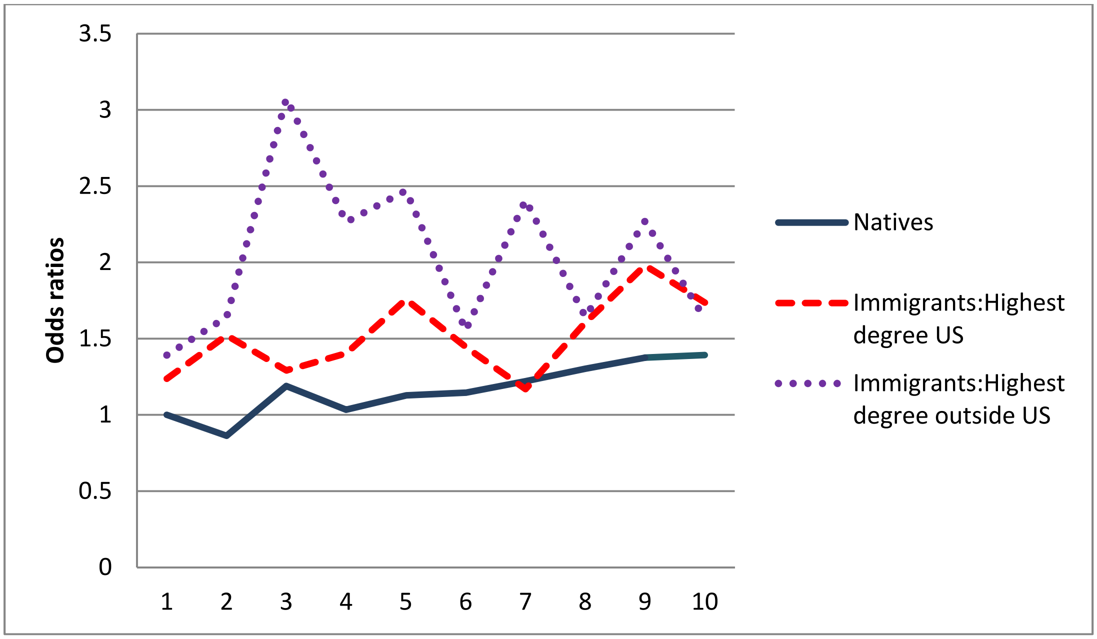
Notes: The values on the vertical axis represent odds ratios from a multinomial logit regression. See Table 5. The reference category is paid employment in the next period. For more details, see text.

Figure 4 Non-Science Entrepreneurship in the Next Period and Deciles of Wage Residuals



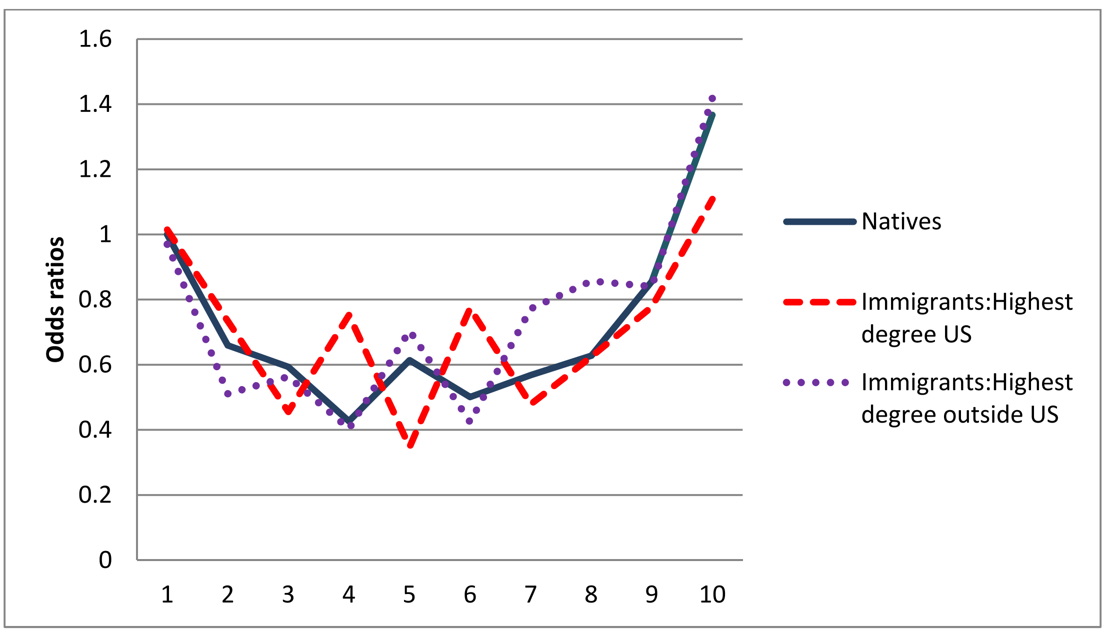
See notes Figure 3.

Figure 5 Science Entrepreneurship in the Next Period and Deciles of Wage Residuals



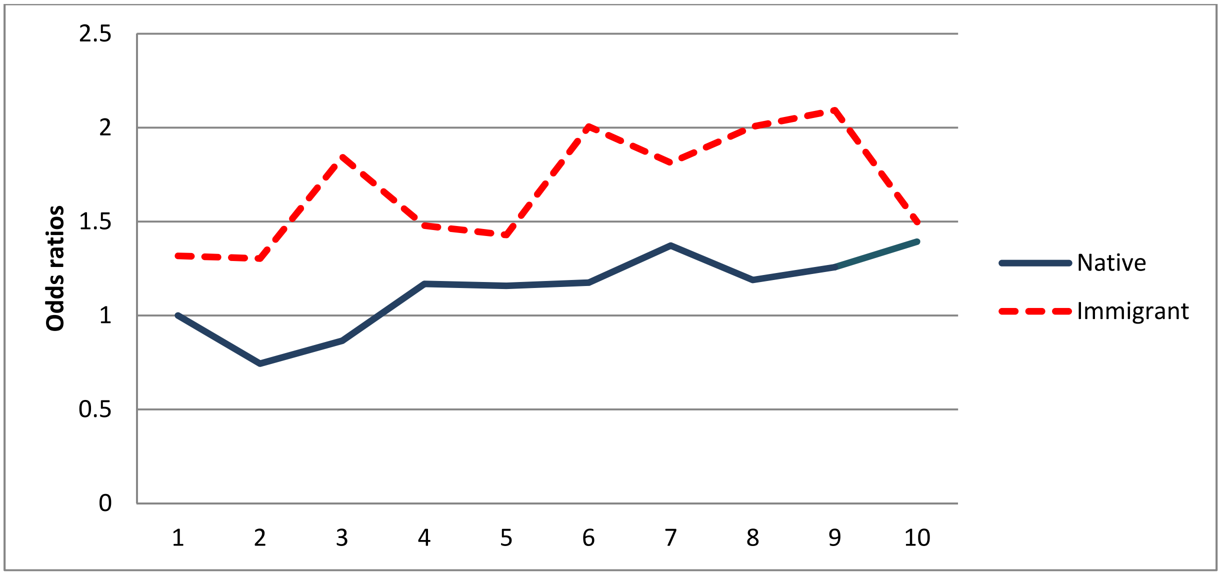
Notes: The values on the vertical axis represent odds ratios from a multinomial logit regression. For more details, see text.

Figure 6 Non-Science Entrepreneurship in the Next Period and Deciles of Wage Residuals



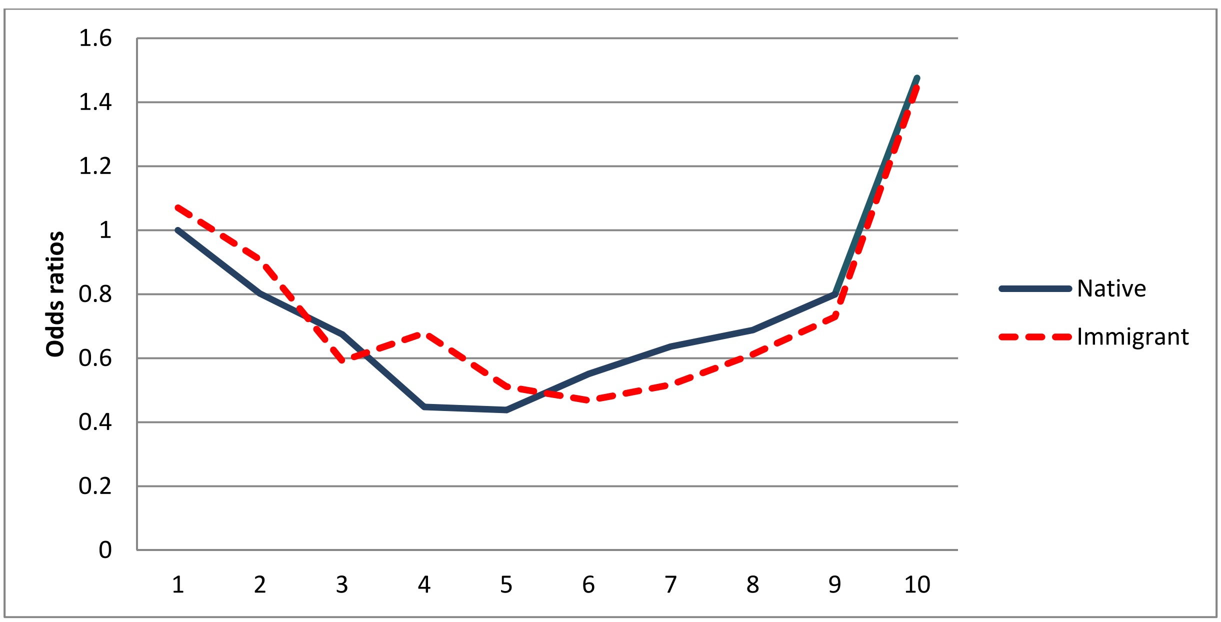
Notes: The values on the vertical axis represent odds ratios from a multinomial logit regression. For more details, see text.

Figure 7 Science Entrepreneurship in the Next Period and Deciles of Wages



Notes: The values on the vertical axis represent odds ratios from a multinomial logit regression. See Table 10. For more details, see text.

Figure 8 Non-Science Entrepreneurship in the Next Period and Deciles of Wages



Notes: The values on the vertical axis represent odds ratios from a multinomial logit regression. See Table 10. For more details, see text.

Appendix: Definition of "Science Entrepreneur"

We define an indicator for being an entrepreneur (self-employed incorporated) in science. The indicator takes the value 1 if any one of the following criteria is met:

- The individual has a job in bio/med science, chemistry, chemical engineering, computer/math sciences, civil engineering, electrical engineering, mechanical engineering, other engineering, other physical sciences, physics or other life sciences and his/her primary work activity is not professional services.
- The individual has a job as a manager and his/her primary work activity is research (Design of Equipment, Processes, Development, Computer Applications, Programming, Basic research, Applied Research); the individual is a manager and his/her primary work activity is management but his secondary work activity is research.

Definition of "Non-Science Entrepreneur"

We define an indicator for being an entrepreneur (self-employed incorporated) but not in science. The indicator takes the value 1 if any one of the following criteria is met:

- The individual has a job in non-science or has a job as a teacher.
- The individual has a job as a manager and neither his/her primary nor secondary work activity is research.
- The individual has a job in bio/med science, chemistry, chemical engineering, computer/math sciences, civil engineering, electrical engineering, mechanical engineering, other engineering, other physical sciences, physics or other life sciences and his/her primary work activity is professional services.