**“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 wage distribution. Using a large panel of US-based scientists, we revisit these findings and establish four new facts about the relationship between ability and high-skilled immigrant entrepreneurship in the United States. First, we find that immigrants are over-represented only in science-based entrepreneurship. Second, after controlling for ability in paid employment as measured by wage residuals, immigrants still have a substantial advantage in science entrepreneurship relative to natives. Third, the previously established U-shaped relationship between ability and entrepreneurship exists only in non-science entrepreneurship; for science entrepreneurship, the relationship is increasing. Finally, the immigrant entrepreneurship premium is largest among immigrants who obtained their highest degrees abroad, or who come from non-English speaking countries and countries that are culturally dissimilar from the US.

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Three types of individuals have consistently been shown to have higher rates of entrepreneurship: immigrants; “stars” at the top of the wage distribution; and “misfits” at the bottom.[[1]](#footnote-1) Research also suggests that immigrants may be overrepresented at the extremes of the ability distribution. 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. This paper asks whether the documented higher rates of entrepreneurship among immigrants – an immigrant entrepreneurship premium – are explained by immigrants’ position 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 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-shape documented in prior studies could reflect heterogeneity in types of entrepreneurship. That is, 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 (STEM), immigrant entrepreneurs may be more likely to be stars.[[2]](#footnote-2) Specifically, in this paper we distinguish 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.

Secondly, we use wage residuals in past employment rather than wages as our measure of ability (although results are robust to a parallel analysis with wages as the key variable). 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. 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 as measured by prior wages. Interestingly, the 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 higher education in the US. 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, our data do not allow us to distinguish this from other potential explanations, and future research on this topic is needed.

**Literature Review**

*Entrepreneurship and ability*

A large part of the literature on the determinants of entrepreneurship concerns the abilities that lead to entrepreneurship or are correlated with entrepreneurship. Those people who are “superstars” 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, Schleifer and Vishny 1991). People with a high level of a variety of abilities – referred to by Lazear (2005) as being a “jack-of-all-trades” – will find their broad skills particularly useful in starting one’s own business.

Empirically, however, higher rates of entrepreneurship are observed at both ends of the 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.[[3]](#footnote-3) The same U-shaped relationship has been identified between wages in previous paid employment and entrepreneurship (Poschke 2013, Elfenbein *et al.* 2010, Braguinsky, Klepper and Ohyama 2012) and between experience and entrepreneurship (Rider *et al.* 2013). [[4]](#footnote-4)

To explain the high rates of entrepreneurship at the bottom of the ability scale, some have suggested determining factors completely different from those at the top. Thus, low-ability entrepreneurs are considered to be people who enter self-employment because they cannot find a job or believe they are under-employed – the “grass is greener” syndrome. The terms “hobo” and “misfit” have been applied to these low-ability entrepreneurs.[[5]](#footnote-5) Several recent papers have developed equilibrium models that predict the observed bimodal relationship between entrepreneurship and ability. These models are all based on some convexity in the relationship between productivity as entrepreneurs and wage in paid employment (e.g. Poschke 2013, Ohyama 2007, Astebro *et al.* 2011).

*Immigrant Entrepreneurship*

A separate stream of research has documented higher rates of self-employment among immigrants than among the native-born, particularly in the US and in high-technology enterprises.[[6]](#footnote-6) 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 observed in the high-technology sector as well. 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 start a firm with more than 10 employees compared to natives.

**Data**

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, Klepper and Ohyama (2012), Ohyama (2011) and Gort and Lee (2007).

SESTAT is collected by the National Science Foundation (NSF) and it 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 has limited coverage of those receiving their highest degree outside of the United States or of those without STEM degrees who work in STEM jobs, but had not been in these jobs when first surveyed (either in the Census or Survey of Recent Graduates.)

SESTAT consists of three surveys, the National Survey of Recent College Graduates (NSRCG), the National Survey of College Graduates (NSCG) and the Survey of Doctorate Recipients (SDR). It created a new panel of scientists each decade from the NSCG, adding in people as they graduated with a bachelor’s or master’s degree (based on the NSRCG).[[7]](#footnote-7) However, PhDs from the SDR were picked up as they graduated, sampled from the NSF’s Survey of Earned Doctorates and followed through both decades. The 1990s SESTAT panel includes 4 waves: 1993, 1995, 1997, and 1999. The 2000s panel also includes 4 waves: 2003, 2006, 2008 and 2010.[[8]](#footnote-8) Each NSCG panel includes a sample of college graduates identified in the 1990 (the 1993-99 panel) or 2000 (2003-10 panel) decennial census who have degrees in science or work in science occupations. Through the decade, subsamples of new graduates from the NSRCG are added to the NSCG panel. The NSRCG includes individuals with a science, engineering or health bachelor’s or master’s degree in the previous two to three academic years. SESTAT includes these recent college or higher graduates as well as science PhD recipients surveyed by the SDR (1993, 1995, 1997, 1999, 2001, 2003, 2006, 2008 and 2010).

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 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 analysis, and this will pick up any difference across surveys due to these compositional factors as well as time-related factors.

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. In 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, Klepper and Ohyama, 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, although we do add robustness checks that model entrepreneurship based on wages rather than wage residuals.[[9]](#footnote-9) 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). We then measure how the probability of becoming an entrepreneur in the next survey – usually two years later – reflects the relative position in the distribution of wage residuals in previous paid employment (as measured by the wage residual decile). Because this estimation involves a two-step process, we bootstrap the standard errors in the two-stage results.

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.

**Summary statistics**

In 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 not (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.[[10]](#footnote-10) 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 half the number of 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.

**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 is U-shaped in wage residuals (or wages). Third, we ask whether immigrants are more likely than natives to be entrepreneurs along the entire range of the ability/wage-residual distribution. Finally, we ask whether the relationship between ability and entrepreneurship is different for science and non-science entrepreneurship, and whether the immigrant-native differences are similar in both sectors.

*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 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.[[11]](#footnote-11) 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 advantage in science entrepreneurship. 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 natives (column 5).

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.

*Is the 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 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.[[12]](#footnote-12) As can be seen in Figure 1, immigrants are disproportionately drawn from the 1st decile of the wage residuals’ distribution relative to natives. As stated in the introduction, this over-representation of immigrants at the bottom of the distribution could reflect differences in ability, discrimination, mismatch in the labor market, lower endowment of unobservable characteristics such as language skills, or other factors. Figure 2 divides immigrants by where they earned their highest degree. This figure demonstrates that 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.

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. 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 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 Column 5 of Table 3, adding dummies for wage residual deciles, where the first decile is normalized to an odds ratio of 1. Because this is a two-step method, standard errors are bootstrapped. 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. The immigrant entrepreneurship premium is not due to the fact that immigrants are distributed differently than natives along the wage residual distribution.

*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 (10th decile) have a much higher (in magnitude and significance) probability of entering non-science entrepreneurship than workers in the 1st decile. Thus, both misfits and stars are overrepresented among non-science entrepreneurs. However, the rate of entry is higher among stars than misfits.

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.

*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. We can reject the hypothesis that the odds ratios associated with the immigrant premium in science entrepreneurship are jointly 1[[13]](#footnote-13) 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. 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. 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.

**Mechanisms**

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

*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.

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. Thus, this 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*.[[14]](#footnote-14)*

*Is the immigrant entrepreneurship premium limited to 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 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. 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. 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. The science immigrant premium for those with a highest degree from abroad is not uniform across the ability distribution; rather, it seems to be driven by those in the middle of the wage residuals’ distribution.

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.

*Is the immigrant entrepreneurship limited to 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.

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.

*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.

**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. This paper has shown the importance of distinguishing between high-technology and low-technology entrepreneurship when analyzing the role of ability in the immigrant entrepreneurship premium. Using wage residuals as a measure of ability, we find that immigrants are significantly more likely to become science entrepreneurs even after controlling for their relative position on the ability spectrum. However, there is no evidence of an immigrant premium in non-science entrepreneurship whether or not we control for wage residuals.

These results also confirm that the misfit/star pattern extends to a highly educated sample, but only in non-science entrepreneurship. We explore the role of preferences for different working arrangements and find that the immigrant premium does not appear to be explained by stated preferences for self-employment.

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 a 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.

**References**

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

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

Åstebro, 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.

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.

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.

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

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.

**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.

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

**Table 1 Self-Employment and Entrepreneurship**

|  |
| --- |
| Panel A: All occupations |
| Percentage of sample who are: | Self-employed incorporated (Entrepreneurs) | Self-employed not incorporated |
|  | Natives | Immigrants | Natives | Immigrants |
|  | 8.93 | 11.07 | 4.80 | 4.52 |
| t-statistics for difference | 20.13\*\*\* | -3.56\*\*\* |
| Panel B: Science |
| Percentage of sample 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-statistics for difference | 36.68\*\*\* | 7.39\*\*\* |
| Panel C: Non-science |
| Percentage of sample 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-statistics for difference | 0.85 | -7.03\*\*\* |

*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. Sample size: 539,565 observations on 260,512 individuals.

**Table 2 Entrepreneurship (self-employed incorporated) in the**

**subsequent period for those in paid employment**

|  |
| --- |
| Panel A: All occupations |
| Percentage of the sample who are: | Entrepreneurs |
|  | Natives | Immigrants |
|  | 4.03 | 4.57 |
| t-statistics for difference | 13.85\*\*\* |
| Panel B: Science |
| Percentage of the sample who are: | Entrepreneurs in science |
|  | Natives | Immigrants |
|  | 1.18 | 2.67 |
| t-statistics for difference | 25.60\*\*\* |
| Panel C: Non-science |
| Percentage of the sample who are: | Entrepreneurs in non-science |
|  | Natives | Immigrants |
|  | 2.85 | 2.75 |
| t-statistics for difference | -1.32 |

*Notes*: Data from 1993, 1995, 1997, 2003, 2006, and 2008 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. Sample size: 310,864 observations on 128,197 people.

**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 | No | No | No | No | Yes | No | No | No | No | Yes |
| characteristics |
| 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 regressionBase 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 logitBase 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*: Coefficients reported as odds ratio. See notes Table 4. Estimates in Columns 1 and 2 are obtained from the same regression.

**Figure 1**

**Figure 2**

**Figure 3**

*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**

*See notes Figure 3.*

**Figure 5**

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

**Figure 6**

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

**Figure 7**

*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**

*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.
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.” [↑](#footnote-ref-1)
2. Hunt and Gauthier-Loiselle (2010). [↑](#footnote-ref-2)
3. 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. [↑](#footnote-ref-3)
4. While Braguinsky , Klepper and Ohyama (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. [↑](#footnote-ref-4)
5. E.g., Astebro *et al.* (2011), Astebro and Thompson (2011). [↑](#footnote-ref-5)
6. Fairlie and Lofstrom (2013) 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. [↑](#footnote-ref-6)
7. Starting in 2013, new SESTAT entrants are drawn from the American Community Survey and added each survey year. [↑](#footnote-ref-7)
8. Since PhDs are followed through both decades, some of them are observed in more than four waves. [↑](#footnote-ref-8)
9. Carnahan *et al.* (2012) also used wage residuals to study the relationship between ability in previous employment and entrepreneurship. [↑](#footnote-ref-9)
10. 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. [↑](#footnote-ref-10)
11. Here, we report the coefficients (as odds ratios) on the immigrant dummy only. Full regression results from this and all tables are available at sites.bu.edu/shulamitkahn/. [↑](#footnote-ref-11)
12. 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%. [↑](#footnote-ref-12)
13. In other words, we reject the joint hypotheses that the immigrant and native coefficients equal each other at each decile. [↑](#footnote-ref-13)
14. 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. [↑](#footnote-ref-14)