“Hobos”, “Stars” and Immigrant Entrepreneurship

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Abstract

We use data from a large survey of scientists and highly educated individuals to study determinants of science and non-science entrepreneurship for immigrants and natives. Conditional on standard factors, immigrants are significantly more likely to become entrepreneurs even after controlling for their relative position on the ability spectrum (measured by wage residuals.) This result is consistent with a Roy model assuming immigrants have high entrepreneurial ability. There is a hobo/star pattern only for non-science entrepreneurship. For science entrepreneurship, only middle and high-ability individuals enter entrepreneurship, consistent with high entry costs. These findings have important implications for immigration policy.

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1. Introduction

Prior studies have established that the ability of entrepreneurs appears to be drawn from a bimodal distribution, with individuals with very low and very high ability levels sometimes denoted as "hobos"[1] and "stars" respectively.[2] Other work has shown that immigrants are more likely than natives to become entrepreneurs.[3] In this paper, we synthesize these two strands of the literature to investigate whether immigrants are entrepreneurs because they are found at the extreme ends of the ability spectrum. In addition, we ask whether ability translates into entrepreneurship in the same way for immigrants as for natives. If immigrant entrepreneurs are disproportionately drawn from the top of the ability distribution, loosening immigration policy for the highly skilled should help lead to economic growth through innovative start-up companies[4]. If, by contrast, immigrant entrepreneurs are mostly drawn from the low end of the ability distribution, arguments for stimulating innovation through immigration policy may be less convincing.

Of particular interest for immigration and innovation policy are entrepreneurial firms engaged in science or engineering, firms that historically have played a key role in developing and commercializing new technologies, and consequently in driving economic growth. The foreign-born are becoming larger and larger proportions of the US science, technology, engineering and math (STEM) workforce, and therefore are likely to start new firms, especially new firms engaged in science or technology, an activity with particularly high ability requirements.[5] Accordingly, we use a sample of highly educated individuals and consider entrepreneurship engaged in science separately from non-science entrepreneurship. We investigate whether immigrants are more likely to start firms engaged in science than natives with similar scientific backgrounds. We also ask whether the hobo/star phenomenon extends to

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[1] We believe that Ghiselli (1974) was the first to use this term in this context.
[2] For instance, see Elfenbein , Hamilton and Zenger (2010).
[3] For instance, Fairlie (2008).
[4] Throughout the paper we define immigrants as foreign born.
[5] See Bound,Turner and Walsh (2009), National Science Board (2012).

a highly educated sample engaged in science entrepreneurship, and whether this is true for both natives and immigrants. We find significant differences in the role of ability in science and non-science entrepreneurship for all individuals. We also find that the "immigrant premium" in entrepreneurship exists at different levels of ability for these two types of entrepreneurship.

2. Immigrant Entrepreneurs and the Determinants of Entrepreneurship

This study is related to the literature that documents the immigrant premium in self-employment and entrepreneurship. Previous authors have noted the greater likelihood of immigrants than natives to be self-employed, particularly in the U.S. Seminal work by George Borjas (Borjas 1986; Borjas and Bronars, 1989) found that the likelihood of self-employment increased the longer the immigrant was in the US and the later the cohort.

Many have noted the relationship between immigrants and scientific/technical entrepreneurship. Hart and Acs (2011) survey the high tech industry and find that 16% of the companies in their sample reported at least one founder who was foreign-born. Wadwha et al. (2007) collected information on engineering and technology companies founded between 1995 and 2005 and interviewed 144 of them. Among other things, they found that 25% had foreign born CEO's or CTO's, 53% of whom completed their highest degree in U.S. universities, and that the majority of these had come to the US to study. Finally, Anderson and Platzer (2006) found that in the period 1990-2005, immigrants started 40 percent of U.S. public venture-backed companies operating in high technology.

Although many researchers have documented the immigrant entrepreneurship premium, the literature has not reached a consensus on the determinants of this premium. Here we mention some of the previous literature of those explanations for this premium addressed in this paper: field, preferences and ability.

The foreign-born are an increasing proportion of U.S. graduates in science at all levels of higher education, particularly at the doctoral level (see Bound, Turner and Walsh 2009, National Science Board 2012) and scientific knowledge may be an important determinant of science entrepreneurship. Hunt (2011) suggests that academic field of study is an important source of immigrant-native differentials in innovation and knowledge creation. Using the National Survey of College Graduates data,[6] Hunt (2001) shows that the advantage of immigrants over natives in patenting and publishing can be largely attributed to the fact that immigrants were more likely to choose science and engineering as fields of study. Hunt's results on entrepreneurship are less conclusive due to a definition of entrepreneurship that included relatively few individuals; combined with the smaller cross section..

A relatively large literature argues that entrepreneurship is a utility maximizing decision that is related to preferences and risk tolerance. Recently, Fairlie and Holleran (2012) investigated the role of preferences and risk tolerance in entrepreneurship using a randomized trial of entrepreneurship training. Some of the others who have contributed to the literature on the relation between entrepreneurship and preferences and/or risk tolerance include Kihlstron and Laffont (1979), Blanchflower and Oswald (1998), and Blanchflower, Oswald, and Stutzer (2001), Kilstrom and Lafont (1979), Caliendo et al. 2009, Verheul et al.. (2012), Evans and Leighton (1989), Sauermann and Cohen (2008), and Cramer *et al.* (2002).

A large part of the literature on the determinants of entrepreneurship concerns the abilities that lead to entrepreneurship or are correlated with entrepreneurship. Thus, those people who are "superstars" may enter entrepreneurship in order to capture their entire marginal product or because of their high return to entrepreneurship is (e.g. Elfenbein 2009, 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, entrepreneurship seems common 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. Poschke (2008) 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

[6] The National Survey of College Graduates is used to derive the SESTAT panel data employed in this paper.

(2004) among others; Astebro et al. has also found a bimodal relationship between entrepreneurship and education. The same U-shaped relationship has been identified between and wages in previous paid employment and entrepreneurship (Poschke 2008, Elfenbein et al. 2009, Braguinsky et al. forthcoming.[7])

To explain the high rates of entrepreneurship at the bottom of the ability scale, some of the literature has suggested determining factors completely different from those that dominate 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 term "hobo" is sometimes applied to these low-end entrepreneurs – borrowed from the job mobility literature – or the word "misfit."[8]

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. Thus Poschke (2008) derives U-shaped entrepreneurship from a search model assuming that expected productivity of entrepreneurs is positive and concave[9] with respect to ability in paid employment and assuming uncertainty in the productivity of any given entrepreneurial project. Ohyama (2007) derives a U-shaped relationship between entrepreneurship and human capital based again on uncertainty of proposed projects; he also assumed convexity in the relationship between a person's cost of acquiring entrepreneurship skills and ability. Ohyama finds that the entrepreneurship choice depends on how strongly human capital (in paid employment) is positively correlated with entrepreneurial capability.[10] Finally, Astebro *et al.* (2011) finds frictions in the paid labor market lead to workers not being efficiently assigned, and thus being underpaid at the top and the bottom due to the concave relationship between entrepreneurship

[7] While Braguinsky , Klepper and Ohyama (forthcoming) 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.
[8] E.g., Astebro *et al.* (2011)
[9] But not too concave.
[10] On the other hand, Braguinsky et al. (forthcoming) has model with a very similar set-up leading to entrepreneurship monotonically increasing with wages as well as other predictions.

productivity and firm quality (where firm quality directly impacts paid employment wages).[11]

Below we consider these potential explanations for the immigrant wage premium in turn.

3. Data

This analysis uses the National Science Foundation's SESTAT database of over 300,000 individuals observed between 1993 and 2006. 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 (forthcoming), 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. We select a sample which contains observations on over 436,441 respondents that have science, engineering, technical, or math (STEM) or related degrees or who work STEM occupations. The biennial panel nature of the data allows researchers to follow scientists and engineers over time.

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. SESTAT has limited coverage of those receiving their highest degree outside of the United States and those that move into science and engineering jobs during the decade.

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

[11] The evidence we show later in this paper that both high and low wage *residuals* increase entrepreneurship seems to be inconsistent with the Astebro model.

Recipients (SDR). It creates a new panel of scientists each decade. The 1990s panel includes 4 waves, 1993, 1995, 1997, and 1999. We use these as well as two waves of data from the 2000s panel (2003 and 2006).[12] Each NSCG panel includes a sample of college graduates identified in the 1990 (the 1993-99 panel) or 2000 (2003-06 panel) decennial census who have degrees in science or work in science occupations. Through the decade, subsamples of the NSRCG are added to the NSCG. 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.

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.[13] 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 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.[14]

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,

[12] The NSCG was not conducted in 2001, although the SDR was.
[13] More information about the SESTAT database is available at http://www.nsf.gov/statistics/sestat/.
[14] For robustness, we have also done most of the analysis excluding health fields and results are qualitatively similar.

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.[15]

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, forthcoming), 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 a science entrepreneurship is given in the Appendix.

Most of our empirical work involves logit regressions of the likelihood of entrepreneurship or multinomial logit regressions of the likelihood of science or non-science entrepreneurship. These results are reported as logit coefficients (thus representing impacts on the log-odd of entrepreneurship). Whenever the analysis included more than one observation per person, standard errors were clustered by person.

In the next section, we compare self-employed incorporated to those who are self-employed non-incorporated, and show that these have very different rates of science entrepreneurship and very different immigrant-native differences.

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[15] Two recent studies of science-related types of entrepreneurship (Hunt, 2011 and Braguinsky *et al.* forthcoming) chose instead to use all self-employment; however, at the same time each excluded a different occupations that were not likely to start a business.

4. Findings on immigrants and entrepreneurship

In 1993-2006 SESTAT, on average 7.6% of workers are classified as entrepreneurs according to our definition (self-employed and incorporated) and an additional 5.3% are self-employed but not incorporated. While the rate of total self-employment is somewhat higher among immigrants than among natives (13.9% compared to 12.8%), as Table 1 shows, this is very different in incorporated compared with non-incorporated self-employment. Immigrants have substantially higher likelihoods of being self-employed incorporated, where 9.1% of foreign-born were entrepreneurs compared to 7.3% of natives which translates into immigrants being 24% more likely than native to be entrepreneurs. In contrast, immigrants are .69 percentage points *less* likely than natives to be self-employed and un-incorporated.[16]

We are most interested in those entrepreneurs (self-employed incorporated) whose new ventures are science-based i.e. *science entrepreneurship.* As Table 1 shows, those self-employed in science are about three times more likely to be incorporated than not. Seen a different way, those who are self-employed incorporated are more likely to be in a science-related business than those who are self-employed non-incorporated (compare 23.0% v. 13.2%)

In *science* entrepreneurship (self-employed incorporated), the difference between natives and immigrants is far more striking (Table 1). Immigrants are almost 100% (3.20 v. 1.62 percentage points) more likely than non-immigrants to be doing science entrepreneurship, while only 3% (5.91 v. 5.72 percentage points) more likely to be doing non-science entrepreneurship. Even among those self-employed non-incorporated, we are more likely to find immigrants to be science entrepreneurs than natives, although these rates our tiny.

4.1. Is the immigrant entrepreneurship premium explained by education, field of study, demographics or time period?

The establishment of an entrepreneurial venture in many cases reflects the commercialization of a new idea. One of the most fruitful sources for profitable new ideas is

[16] Due to the large sample size, this difference is significant at the .01% level. The same is true for small differences discussed in the following paragraph.

recent scientific knowledge (whether discovered by the potential entrepreneur or not). It is possible that the immigrant-native differential in entrepreneurship and particularly in science entrepreneurship is due mainly to educational attainment or field of study.

In our sample, immigrants are 161% more likely than natives to have a PhD (11.3% v. 4.3%), 19% more likely to have a (non-MBA) Master's degree (32.0% v. 26.8%) and 77% more likely to have an MD (4.5% v. 2.5%). Similar proportions of natives and immigrants have MBAs (6%).

Table 2 displays the distribution of natives compared to immigrants across the detailed field of highest degree. We find that immigrants are twice as likely as natives to be in computer and information science and are almost twice as likely as natives to be in engineering. Immigrants are about half as likely to be in social sciences, and 50% as likely to be in a field besides science and engineering. In a logit estimation of the probability of entrepreneurship (self-employed and incorporated), field alone can explain 2.1% of the variation in entrepreneurship. In results not shown (available upon request), the fields that are most likely to lead to science entrepreneurship are computers and IT, physical or material sciences, and earth sciences; to a lesser degree, the list would civil engineering, electrical engineering, industrial and mechanical engineering, and business. Fields that are least likely to lead to science entrepreneurship are biological sciences (including microbiology, biochemistry and others), social sciences (including clinical psychology, and health).[17]

In the first three columns of each panel of Table 3, we investigate whether field of study and educational attainment alone explain the immigrant-native gap in overall entrepreneurship status. The three panels of Table 3 model total entrepreneurship, science entrepreneurship and non-science entrepreneurship respectively.

Panel A column 1 shows that on average, the coefficient on immigrant implies that immigrants are approximately 26% more likely[18] (1.9 percentage points (ppt.)) to be entrepreneurs than natives. When the level of education is controlled for, immigrants' advantage

[17] This list of fields is similar when more covariates are added.
[18] Calculated as exp(.236).

in entrepreneurship increases (although not significantly). The increase is primarily due to the fact that immigrants are more likely to have a PhD and non-MBA masters, both which can be seen in Table 3 to decrease the chances of being an entrepreneur.[19] With controls for both field and education (column 3), immigrants are approximately 31% more likely to be entrepreneurs than natives.

As we learned in Table 1, the unconditional immigrant premium is present in science entrepreneurship only. A comparison of immigrant coefficients from Table 3 column 1 Panels B and C indicate that immigrants are twice as likely to be science entrepreneurs as natives but only marginally more likely to be non-science entrepreneurs.[20] However, a major reason for this is the relation between entrepreneurship and field. Controlling for field and education substantially reduces the immigrant coefficient while increasing the immigrant coefficient in non-science entrepreneurship to a statistically significant 0.15 (16% odds ratio). Further, one notes that in both columns 2 and 3 the coefficients on educational degree are quite different between science and non-science entrepreneurship and the same is true for the coefficients on fields (not shown). This again emphasizes the difference in the nature of science and non-science entrepreneurship.

Part of the reason that immigrants and natives have different rates of entrepreneurship (particularly the science type) may be due to demographics and differences in family structure between these groups. Column 4 adds dummies for gender, age, race and family structure. Most notably, females are more than 40% less likely than males to be entrepreneurs of either kind. Family factors affect science and non-science entrepreneurship differently: marriage and children increase men's likelihood to enter non-science entrepreneurship but children impede men's likelihood to be science entrepreneurs and marriage has no effect; children significantly impede women's non-science entrepreneurship only; and having a working spouse only increases a person's likelihood of science entrepreneurship. Adding these variables decreases the immigrant

[19] Note that the fact that PhDs decrease entrepreneurship is different from what Poschke (2008) found using the NLSY, i.e. that PhDs are more likely to be entrepreneurs than all other educational levels.
[20] Note that column 1's impact of immigrant status are not exactly the same as was seen in the averages of Table 1, both because science and non-science entrepreneurship here are modeled jointly and because of the non-linear nature of logit analysis.

premium in science entrepreneurship and slightly (but insignificantly) increases it in non-science entrepreneurship.

Finally, in column 5, survey year dummies are added.[21] Science entrepreneurship is strongest in the 2000s and weakest in the first survey year 1993; survey year has smaller effects in non-science entrepreneurship. Survey year dummies seem to mitigate immigrant-native differences by only a small and insignificant amount.

In sum, even with all of these controls, immigrants remain 31% (.50 ppt) more likely than natives to be science entrepreneurs and 19% (1.1 ppt) more likely to be non-science entrepreneurs.

Because foreign degrees may imply a different kind of education than US degrees, may be perceived by employers to be different, and/or may be less understood by US employers, we also separately analyze those immigrants whose highest degree was awarded in the US compared to abroad in columns 6 and 7. Unconditionally (column 1), those who received their highest degree in the US have somewhat lower science entrepreneurship rates than those who received their degree abroad in the US and had lower non-science entrepreneurship rates than even natives. However, once all the other factors are controlled for (column 7), the differences in entrepreneurship rates between immigrants with and without US degrees is shown to be small, with those with highest degrees in the US having more science and non-science entrepreneurship.

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

In 1997, SESTAT collected data about individuals' preferences for different working arrangements rather than for different job characteristics. 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 4, we model the probability of entrepreneurship (self-

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[21] Note that we do not include region in any of our entrepreneurship models because region is itself endogenous, particularly science entrepreneurship since those interested in starting a company are likely to move to a center of innovation such as Silicon Valley.

employed incorporated) as a function of a dummy variable for whether workers preferred self-employment as well as all explanatory variables from the previous table. We first re-estimate the final model of Table 3 on this smaller sample with no preference variable but with other explanatory variables. We then add the preference variable in the final three columns.

As expected, a higher 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.[22] Of most interest to this paper, adding the preference for self-employment reduces the immigrant premium by only 9%. 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.) Thus, this further suggests that something other than preferences, educational level or field, or family structure is responsible for the fact that immigrants are more likely than natives to be entrepreneurs, particularly but not exclusively science entrepreneurs. We therefore turn to ability and wage-based explanations.

5. Entrepreneurship and ability in paid employment: theoretical framework

Given that field, education, demographics and preferences do not fully explain the immigrant entrepreneurship, we now consider the empirical and theoretical relationship between ability and entrepreneurship.

Below we illustrate a Roy model of occupational choice that helps to describe the relationship between ability in paid employment and entrepreneurship. The model we describe is a similar to a stripped-down version of the models of Poschke (2012) and Ohyama (2007). In our model, ability in entrepreneurship is positively correlated with ability in paid employment, but the nature of this correlation determines whether people select into entrepreneurship or paid employment. Rather than specifying a single specific motivation that mathematically yields non-

[22] This analysis is run on people who presently were or were not entrepreneurs. It is possible, however, that people change their preferences for entrepreneurship after they enter it, or at least believe they do because of cognitive dissonance. We have repeated this analysis using preferences for the subset presently in paid employment in 1997 to predict whether the person enters entrepreneurship in 1999, with similar qualitative conclusions.

convexities in the Roy boundary between entrepreneurship and paid employment like those articles, we assume non-convexity based on some basic observations about correlation between these abilities.

After laying out our basic model, we speculate about how the distribution of these skills, and/or the rewards to these skills, are likely to be different in immigrants and natives in ways that affect the likelihood of entrepreneurship. Also, we speculate about how these factors may differ between science and non-science entrepreneurship.

People enter entrepreneurship if the expected return from entrepreneurship is greater than the expected return from paid employment. Assume two sectors, paid employment (pe) and entrepreneurship (se). Let H be human capital characteristics (such as education and experience) that influence productivity in paid employment and self-employment in the same way and γ be their coefficients (in both sectors).[23] In contrast, let M be an index of characteristics that increase productivity in paid employment only, while R is an index of characteristics that increase productivity in entrepreneurship only. In measurement terms, we think of M as abilities such as teamwork skills and the ability to accomplish tasks in a timely fashion. In contrast, R includes characteristics such as resourcefulness, risk-tolerance or optimism particularly useful for entrepreneurship.

Consider the choice facing individual i who is presently employed by an established firm and paid an income:

$$Y_{i,pe} = H_i\gamma + w_{pe} M_i$$

If the individual becomes an entrepreneur, the income would be:

$$Y_{i,se} = H_i\gamma + w_{se} R_i$$

The individual will choose to become an entrepreneur iff:

$$w_{pe} M_i > w_{se} R_i$$

Here, we define the units of M and R such that the returns (w_{pe}) to each unit of M and the returns (w_{se}) to each unit of R respectively are constant.

[23] The assumption that the return to human capital in paid employment is exactly the same as the return to human capital in self-employment is quite strong.

Whether people with the highest or lowest ability in paid employment (M) enter entrepreneurship depends on the correlation between the individual's endowment of M and R relative to the returns to M and R respectively. To see this, consider Figures 1a and 1b. Here, we assume the simplest possible model of productivity with no fixed cost of entering entrepreneurship. The solid line in each figure represents $w_{pe} M_i = w_{se} R_i$, or $R_i = w_{pe} / w_{se} M_i$. People with endowments above this line will become entrepreneurs, and those with endowments below this line will take paid employment.

For simplicity, we hypothesize that individuals' actual endowments of M and R can be described as limited to the M/R combinations along the dashed lines in each Figure. More generally, imagine a distribution of endowments centered around these lines. In Figure 1a, people with high M have particularly high R. In this case, entrepreneurship attracts only the most able people who have high levels of both R and M.

In contrast, in Figure 1b, R is much less positively correlated with M, so that endowments of R appear quite similar across all levels of M. Here, people at all levels of M_i have the level of R needed to become good entrepreneurs. However, this does not mean that all people are equally likely to become entrepreneurs. Instead, it is only those who are paid particularly poorly in paid employment with respect to their human capital that enter entrepreneurship. Note that this is the case as long as the line characterizing the relative skill endowments (the dashed line in the figure) is flatter than w_{pe} / w_{se}. In fact, R and M could even be negatively correlated.

Which of these figures is most likely to capture the true relation between skills useful to entrepreneurship and skills useful to paid employment? *A priori*, how do we expect endowments of M and R to be distributed (relative to the returns to these endowments)?

First, the low rates of entrepreneurship suggest that a large proportion of people have low levels of R.

Second, the model of Lazear (2005) suggests that those at high levels of ability in paid employment (controlling for education, experience etc.) are likely to also have traits valuable in entrepreneurship, to be Jacks-of-All-Trades.

Together, these two conjectures lead to a convex pattern of endowments as pictured in

Figure 1c. Here, the level of R is relatively constant at low levels of M but rises rapidly at high levels. In this case, we see two kinds of people entering entrepreneurship. Those at low levels of M receive low levels of income in paid employment and are therefore likely to choose entrepreneurship (the hobos). Those at very high levels of M are the Jacks-of-all-trades who also enter entrepreneurship (the stars). In between are people with typical abilities in paid employment who find it more advantageous to remain there. The model therefore predicts a U-shaped relationship between entrepreneurship and ability in paid employment.

How would the model differ for immigrants and natives? We suggest two possible ways, one related to the pattern of endowments of M relative to R, and one based on the return to skills in paid employment.

First, immigrants may have a larger endowment of R than natives. In other words, Figure 1c's dashed line showing the endowments of R and M is shifted up for immigrants. There are a variety of potential reasons for this. 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 have already learned that risk tolerance is associated with entrepreneurship.[24] Indeed, the mere fact that immigrants have left their home countries suggests a heightened ability for change and independence.

How would immigrants' larger endowment of R change our predictions? The endowments distribution would shift up as shown in Figure 1d. As a result, immigrants are more likely to enter entrepreneurship at all levels of M.

Finally, how might the model differ for science entrepreneurship? First, the barriers to entry into science-based entrepreneurship are higher than the barriers to entry into non-science

[24] Interestingly, we found in the previous section that immigrants and natives have similar professed preferences for self-employment. This together with Jaeger et al.'s study imply that risk tolerance increases immigrants' propensity to become entrepreneurs but not their preferences for it.

entrepreneurship. If one thinks of the typical non-science entrepreneur as opening a restaurant, dry-cleaners or doctor's office, it is likely to require less investment than a high-tech or biomedical firm or a firm engaged in new product development. Moreover, science entrepreneurship may require the creativity and imagination necessary to develop a marketable scientific idea which would require a high level of R. We model this as a cost of entry F into science entrepreneurship:

$Y_{i,se} = H_i\gamma + w_{se}(R_i - F)$

Now the condition for entering entrepreneurship is:

$R >= F + w_{pe} / w_{se} M$

In this case, the line separating entrepreneurs and paid employees shifts up.

Moreover, similar reasoning would argue that the return to R, w_{se}, would be particularly high in science entrepreneurship, flattening the slope of the payoff (w_{pe} / w_{se}).

Figure 1e illustrates the predictions for science entrepreneurship. The line graphing the division between entrepreneurs and employees has shifted upwards and flattened. As a result, more people enter science entrepreneurship at the top of the paid-employment (M) ability spectrum.

In the following sections, we consider how this model may be tested empirically.

6. Entrepreneurship and ability in paid employment: empirics

In this section, we investigate some of the implications of the model. First, we ask whether a U-shaped relationship exists between entrepreneurship and ability in paid employment. Second, we ask whether immigrants have more entrepreneurship than natives along the whole range of the ability distribution. Finally, we ask whether the relationship between ability and entrepreneurship is different between science and non-science entrepreneurship, and whether the immigrant-native differences are similar in both sectors.

Previous studies that analyzed the empirical relationship between ability in paid employment and entrepreneurship, summarized earlier, 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.[25] In the model, to the extent that H_i i.e. human capital is measured by the variables in standard wage equations, the wage residuals will represent $w_{pe} M_i$. Note that in addition to being more consistent with our model, we show in the section on robustness tests that a model with wage residuals fits better than one with wages.[26]

To calculate wage residuals, we first estimated a (log) wage equation on the sample of natives[27] working in full-time paid employment using a median regression.[28] Control variables included those used earlier plus experience (linear, squared and cubic) and region of residence.[29] We calculate wage residuals by applying this equation to all people in our sample (i.e. including immigrants).

We then modeled 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,[30] as a function their paid-employment wage-residual decile dummy variables in addition to the Table 3 set of covariates. 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.

Note that until this point, we have not exploited the longitudinal aspect of SESTAT. Using the longitudinal aspect requires that we include only people who were observed (at least) twice, the first while working in paid employment. People first seen in the 1999 and 2006 waves of the sample could not be included because they were never observed a subsequent survey. People are included only one time, the first time they were observed working. We excluded people from the sample if they were already entrepreneurs the first time we observed them. The

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[25] To our knowledge, few prior articles have linked wage residuals to self-employment. One example is Carnahan et al., 2012.
[26] For a wage residual approach to discrimination see Oaxaca (1973) and Blinder (1973).
[27] Similar results were obtained using a wage equation including natives and immigrants estimated without a control for immigrant.
[28] Using Least Absolute Deviations regression (LAD). An OLS model of ln(wages) gives very similar results.
[29] We also tried a different specification that controlled for hours worked in a week and weeks worked in a year. The results were very similar.
[30] There was a three- year gap between 2003 and 2006. Also, a few people might have not responded in one year of the survey, leading to a larger gap. There is a very low non-response rate in SESTAT.

second row of Table 1 gives the size of this 2-period sub-sample and average likelihood of becoming an entrepreneur during the next period in this sample. This sample is approximately half the size of 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 average relationships were the same: immigrants are much more likely to become entrepreneurs than natives, with a much more marked difference in science than in non-science entrepreneurship.

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

Figure 2 shows how immigrant and native workers are distributed across the ten deciles of the wage residuals' distribution. Figure 3 divides immigrant by where they earned their highest degree. These figures demonstrate that immigrants are more likely to be in the first and to a lesser extent the second decile of the wage residuals distribution, particularly immigrants who did not earn their highest degree in the US.

The mere fact that immigrants are more likely to be in the bottom of the wage-residual distribution deciles can contribute to an immigrant-native wage differential if entrepreneurship is more common at the lower extremes of the ability distribution. If higher rates of entry into entrepreneurship by low-ability immigrants are what drives the immigrant premium, it would suggest that greater rates of immigration will not necessarily lead to more high-tech innovation.

In Table 5, we re-estimate the model from Table 3 adding dummies for wage residual deciles; we report the coefficients on immigrant and wage residual deciles only.[31]. Because we are using a sub-sample of our previous sample and estimating entry into entrepreneurship rather than overall entrepreneurship, in columns 1, 3 and 5 we first re-estimate the model with no wage residuals but with the explanatory variables from all previous tables, first for all entrepreneurship and then for science and non-science entrepreneurship (with the latter two estimated jointly using multinomial logit). We then add the wage residuals variables in columns 2, 4 and 6.

[31] The entire regressions from Table 5 and all other tables are available from the authors on request, as are all regressions mentioned but not reported in any table.

Incorporating wage residuals has very little impact on the immigrant premium. In non-science entrepreneurship, the point estimates of the coefficients fall by 15 % (from 0.2156 to .1843, a statistically insignificant change). In science entrepreneurship, the coefficient is basically unchanged.

In results not shown, we repeat the analyses of Table 5 with immigrant separated by whether their highest degree was from the US and find very similar results. Despite the facts displayed in Figure 3, that is, that the mass for the lowest deciles occurs only for those obtaining their degree outside the US, adding wage residual deciles to the set of predictors of science entrepreneurship leaves the two immigrant coefficients (with or without highest degree in the US) virtually unchanged, while in non-science entrepreneurship both coefficients drop by 14-15%.

6.2. Is there a different relationship between entrepreneurship and wage residuals in science and nonscience?

The coefficients on the wage residuals from Table 5 (columns 4 and 6) are illustrated in Figure 4. Note that the coefficient of the first decile is normalized to zero. There is a clear J-shaped pattern in entry into non-science entrepreneurship as a function of wage residuals. Thus, workers whose wage residual falls in any decile between the second and the eighth have a significantly lower probability to enter non-science entrepreneurship than workers who are in the very bottom (first decile) of the residual distribution. 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 to enter entrepreneurship than workers in the 1^{st} decile. Thus, both hobos and stars are overrepresented among entrepreneurs. However, the rate of entry is higher among stars than hobos.

If we were using wages or education as our measures of ability instead of wage residuals, we might expect to observe less of a spike at low wage deciles than observed by studies such as Poschke (2008), because the SESTAT sample is positively selected with respect to education. In other words, in Figure 1c, it could mean that the very bottom of the R, M endowments curve is cut off. The fact that we also observe this J-shape in wage *residuals* in non-science entrepreneurship suggests that it is quite possible to have low levels of M (characteristics besides education etc. that make a person a good paid employee) even with high education and therefore presumably higher wages than most. This itself indicates the value of using wage residuals in our models.

In contrast, for science entrepreneurship, there is *no* evidence of a J or U-shaped pattern in entrepreneurship as the wage residual increases. There is however an upward slope, with a highly significant increase at the 10th decile. This too is consistent with our model, which suggests that because of a fixed cost in entering science entrepreneurship, entrepreneurship occurs towards the top of the paid-employment-ability (M) spectrum.

In results not shown, the analysis was repeated for the subsample of people whose highest degree was in science. The pattern of wage residuals in non-science and science looked very similar to that shown in Figure 3.

6.3. Is the relationship between ability in paid employment and entrepreneurship different for immigrants and natives?

In Table 5, we observed that immigrants are more likely to become entrepreneurs than natives, even holding constant their position in the distribution of wage residuals. However, are immigrants uniformly more likely to become entrepreneurs, or instead is the immigrant premium concentrated in certain parts of the wage residual distribution? If our model is accurate, we would expect more immigrants than natives at the bottom and at the top of the distribution of the paid-employment-ability (M) spectrum, with the top and bottom broadening their range of M values to include more people (see figure 1d).

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 zero). Table 6 contains the results of a logit regression of entering entrepreneurship in the next period on the same controls as in Table 3 plus these two sets of interaction terms. As before, the first column models entrepreneurship as a whole and the next two columns estimate science and non-science entrepreneurship estimated jointly with multinomial logit. A test of the hypotheses of the existence of a wage premium at each residual decile is given in Table 6A. Finally, Figure 5 plots the coefficients of the interaction terms in the last two columns i.e. for science and non-science entrepreneurship.

As before, the patterns are quite different when we look at science and non-science entrepreneurship. In Figure 5, immigrants appear to have higher levels of science entrepreneurship at all deciles. Table 6A indicates that this immigrant gap is significant at differing levels (p=.1 or less) for deciles 2-9, with the exception of decile 3 where p=.104. It is not significant at figures 1 and 10, which runs counter to what the model predicted.

On the other hand, both immigrants and natives seem to have a pattern of increasing science entrepreneurship as wage residuals rise. We also tested this directly by estimating the probability of science entrepreneurship as a function of the wage residual decile (1,2,3 etc.) or of actual wage residuals (entered linearly). In either version, both natives and immigrants had upward sloping relationships between science entrepreneurship and wage residuals with $P < .03$ (for residuals) and $P<.001$ (for residual decile).

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.

Again, Table 6B tests the immigrant premium at each decile. In science entrepreneurship, the gap is only significant at decile 2. Thus, while we know from Table 5 that overall immigrants have a higher probability of entering non-science entrepreneurship after separately controlling for the residual deciles, we see that when the immigrant residual categories are broken into ten different coefficients, the difference is only large enough to be significant at decile 2 (though it remains positive across all deciles except the 10^{th}).

7. Robustness Checks and Extensions

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, with the coefficients on immigrants' and natives' wages decile given in Table 7 and graphed in Figure 7. The pseudo-R-squared (given) and correspondingly the log likelihood are higher when based on wage residuals rather than wages for all three columns, suggesting that if one or the other must be chosen, the estimates using wage residuals should be chosen. On the other hand, if we put wage residual deciles and wage deciles on the right-hand-side simultaneously, we can reject the hypothesis that wages affect science entrepreneurship controlling for wage residuals, but cannot reject this hypothesis for non-science entrepreneurship. We note, however, that the patterns in Figure 5 are similar to those in Figure 6, with the exception of some noisy decile coefficients in Figure 6.

A second alternative would be to model those immigrants with their highest degree in the US compared to those with their highest degree abroad. We saw previously that controlling for field, education, demographics, and year, immigrants who obtained their highest degrees in the US and immigrants who obtained their highest degree abroad were not very different in their rates of either science or non-science entrepreneurship. Although significantly different, translating the difference to percentage points, those with the highest degree from an institution in the US had a .05 percentage point higher science entrepreneurship rate and a .03 percentage higher non-science entrepreneurship rate.

We have also re-estimated the analysis of Table 6 (Figure 5) with three sets of residual dummies, for natives, immigrants with a US highest degree and immigrants with a non-US highest degree. The residuals are graphed in Figure 7. For science entrepreneurship, both sets of immigrants have generally higher entrepreneurship rates. The particular shape for immigrants with the highest degree abroad mirrors the shape for immigrants from Figure 5. Also, the great advantage of immigrants from Figure 5 is shown in Figure 7 to only apply to those with the highest degree from the US.

For non-science entrepreneurship, the figures are very noisy and show no systematic differences between the two types of immigrants.

Finally, in analysis not shown, we have also divided immigrants by whether they came from culturally similar backgrounds; by whether they came from English-speaking countries;

and by whether they went to a US high school. None of these were consistently useful in predicting entrepreneurship.

8. Conclusion

We use data from a large longitudinal survey of US-based scientists to study the determinants of science and non-science entrepreneurship for immigrants and natives. Individuals at the extremes of the ability distribution – sometimes referred to in the literature as "hobos" and "stars" -- have been shown to be more likely to become entrepreneurs. The literature has also uncovered an "immigrant premium" in entrepreneurship. Is the immigrant entrepreneurship premium thus explained by the greater tendency of immigrants to be located at the extremes of the ability distribution? The answer is no. Using wage residuals as a measure of ability, we find that immigrants are significantly more likely to become entrepreneurs even after controlling for their relative position on the ability spectrum. This result is consistent with the predictions of a Roy model under the assumption that immigrants are more endowed with resourcefulness – or other characteristics that are related to productivity in the entrepreneurial sector. These results also confirm that the hobo/star pattern extends to a highly educated sample, but only to non-science entrepreneurship. For science entrepreneurship, we find that only high-ability individuals enter entrepreneurship, consistent with high fixed costs of entry. Furthermore, the immigrant premium in science entrepreneurship is statistically significant at the middle and the top of the wage residuals' distribution, in other words, at higher ability levels.

Methodologically, we also find that wage residuals, rather than wages or education, are better predictors of entrepreneurship. Since wage residuals capture unobserved productivity characteristics, this is consistent with the importance for entrepreneurship of a form of resourcefulness that cannot be quantified with conventional measures of human capital.

The findings from this paper have important 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. There is widely-known evidence that immigrants to the US are more likely to have studied science and engineering than natives, which is important for growth. However, the current paper adds to this literature by finding that even controlling for educational field and level, immigrants are particularly likely to enter science entrepreneurship compared to natives. In terms of entry into science entrepreneurship, there may be a slight advantage for immigrants who receive a degree in the US, but the difference is small – a 5% increase in entrepreneurship due to a US degree when compared to immigrants who receive degrees outside the US.

From the evidence on wage residuals, on the one hand we learn that science entrepreneurship is greatest for people with particularly high ability given their education and other measurable characteristics such as experience. While this is true for both natives and immigrants, it suggests that the more the US can attract stars – even ones not presently engaged in entrepreneurship – the better. On the other hand, our evidence shows that the likelihood that immigrants whose highest degree is not from a US institution enter science entrepreneurship is particularly high at intermediate levels of wage residuals, suggesting the importance of the "medium" talented in this group. Our evidence suggests that while the US should aim to attract highly educated immigrants, the ideal level of educational attainment to foster entrepreneurship is below the PhD level. Also, fields most likely to lead to science entrepreneurship are computers and IT, physical or material sciences, and earth sciences; to a lesser degree, some kinds of engineering (civil, electrical engineering, industrial and mechanical engineering), and business. Immigrants whose training is in the biological or social sciences are not disproportionately likely to become entrepreneurs.

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Table 1 Self-employment and Entrepreneurship

	% of natives who are:	% of immigrants who are:	% of natives who are:	% of immigrants who are:	% of natives who are:	% of immigrants who are:
Incorporated:	Self-employed incorporated		Self-employed incorporated in science		Self-employed incor-porated in non-science	
Sample: Everybody	7.33***	9.11***	1.62***	3.20***	5.72***	5.91***
Sample size	351,755	84,686				
Sample for stage 2 logit (entrepreneurship in t+1)	3.26***	4.82***	0.88***	2.10***	2.38***	2.72***
Sample size	174,377	40,450				
Not Incorporated:	% of natives who are:	% of immigrants who are:	% of natives who are:	% of immigrants who are:	% of natives who are:	% of immigrants who are:
	Self-employed not incorporated		Self-employed not inc. in science		Self-employed not inc. in non-science	
Everybody	5.45***	4.76***	0.65***	0.92***	4.80***	3.84***
Sample size	351,755	84,686				

- Sample: 1993-2006 SESTAT. Only full-time workers are included in the sample.
- *Native/immigrant difference statistically significant at the 10% level **5% level ***1% level

Table 2 Field of Study

Field of highest degree	% of natives	% of immigrants
Computer and Information science	5.09	10.26
Mathematics and Statistics	3.49	3.45
Engineering	15.17	28.03
Biology	6.24	6.31
Physics, Chemistry, Earth Science and others	7.96	8.1
Social sciences	24.31	13.68
Health Sciences	7.75	10.57
SE related	2.53	2.79
Non-SE	18.9	9.22
Business	8.56	7.59

- Sample: 1993-2006 SESTAT. Only full-time workers are included in the sample.
- Standard errors in parentheses are clustered at the individual level.
- Engineering includes aerospace engineering, chemical engineering, civil engineering, electrical and related engineering, industrial engineering, mechanical engineering and other engineering. Biology includes biochemistry and biophysics, microbiology and microbiology & bacteriology and other biological sciences. Physics, chemistry, earth science and others includes environmental sciences, physics, astronomy, other physical sciences, meteorology and atmospheric sciences, other physical & earth sciences, chemistry, geology, zoology, agricultural and food sciences. Social sciences include economics, psychology, other social sciences, political sciences, clinical psychology, sociology and anthropology.

Table 3 Immigrant premium and education level and field

Panel A: All Entrepreneurship

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Immigrant	0.2363***	0.2526***	0.2666***	0.2356***	0.2144***		
	(0.0289)	(0.0306)	(0.0311)	(0.0390)	(0.0389)		
Immigrant highest degree in US						0.0669*	0.2446***
						(0.0347)	(0.0422)
Immigrant highest degree NOT in US						0.4837***	0.1748***
						(0.0425)	(0.0543)
Master's degree		-0.5639***	-0.6740***	-0.7292***	-0.7581***		-0.7612***
		(0.0359)	(0.0386)	(0.0383)	(0.0387)		(0.0388)
Doctorate		-0.9512***	-0.9220***	-1.1436***	-1.1464***		-1.1498***
		(0.0550)	(0.0569)	(0.0573)	(0.0580)		(0.0582)
M.B.A.		0.4506***	0.7892***	0.7927***	0.8961***		0.8958***
		(0.0632)	(0.1088)	(0.1095)	(0.1100)		(0.1100)
M.D.		1.6888***	1.5995***	1.3000***	1.2619***		1.2618***
		(0.0471)	(0.0752)	(0.0778)	(0.0777)		(0.0777)
Black				-0.6128***	-0.6351***		-0.6375***
				(0.0633)	(0.0634)		(0.0634)
Asian				0.1393***	0.1061**		0.1084**
				(0.0452)	(0.0452)		(0.0453)
Hispanic				-0.2115***	-0.2841***		-0.2844***
				(0.0579)	(0.0575)		(0.0575)
Female				-0.3546***	-0.4085***		-0.4081***
				(0.0618)	(0.0620)		(0.0620)
Age				0.1963***	0.2760***		0.2765***
				(0.0443)	(0.0452)		(0.0452)
Age squared				-0.0321***	-0.0496***		-0.0497***
				(0.0098)	(0.0100)		(0.0100)
Age cubed				0.0020***	0.0032***		0.0032***
				(0.0007)	(0.0007)		(0.0007)
Married				0.1078**	0.1503***		0.1507***
				(0.0499)	(0.0500)		(0.0500)
Has child				0.0523	0.0211		0.0219
				(0.0346)	(0.0347)		(0.0347)
Female*married				0.0746	0.0482		0.0488
				(0.0741)	(0.0742)		(0.0742)
Female*child				-0.2326***	-0.2180***		-0.2176***
				(0.0655)	(0.0657)		(0.0657)
Spouse works				0.0137	-0.0012		-0.0011
				(0.0315)	(0.0317)		(0.0317)
Survey year 1995					-0.0840***		-0.0843***
					(0.0300)		(0.0300)
Survey year 1997					-0.1154***		-0.1160***
					(0.0331)		(0.0331)
Survey year 1999					-0.1165***		-0.1175***
					(0.0357)		(0.0357)
Survey year 2003					0.6790***		0.6793***
					(0.0371)		(0.0371)
Survey year 2006					0.8357***		0.8356***
					(0.0365)		(0.0365)
Constant	-2.5365***	-2.4919***	-2.6313***	-6.4758***	-7.9841***	-2.5365***	-8.0014***
	(0.0150)	(0.0178)	(0.0508)	(0.6366)	(0.6527)	(0.0150)	(0.6525)
Includes field of highest degree?			yes	yes	yes		yes
Observations	436,441	436,441	436,441	436,441	436,441	436,441	436,441
Pseudo R-squared	0.000937	0.0364	0.0462	0.0713	0.0889	0.00182	0.0890

Footnotes Table 3

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Excluded categories are BA only, computer/information science, 1993.

The 29 dummies for field of highest degrees are: mathematics and statistics, aerospace engineering, chemical engineering, civil engineering, electrical and related engineering, industrial engineering, mechanical engineering, other eng. sciences, biochemistry and biophysics, microbiology & bacteriology, other biological sciences, environmental sciences physics and astronomy, meteorology and atmospheric sciences, ther physical & earth sciences, chemistry, geology, economics, psychology, clinical psychology, political science, sociology and anthropology, other social sciences, health sciences, zoology, agricultural and food sciences, science and engineering (SE) related, other non-SE, business..

Science and Non-Science Entrepreneurship estimated together using multinomial logit.

Logit coefficients estimating exp(Dummy=1/Dummy=0)

Table 3 Panel B: Science Entrepreneurship

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Immigrant	0.7019***	0.7566***	0.4834***	0.3217***	0.2671***		
	(0.0422)	(0.0427)	(0.0437)	(0.0548)	(0.0557)		
Immigrant highest degree in US						0.6329***	0.2874***
						(0.0492)	(0.0616)
Immigrant highest degree NOT in US						0.8152***	0.2409***
						(0.0620)	(0.0736)
Master's degree		-0.1797***	-0.1593***	-0.2087***	-0.2324***		-0.2357***
		(0.0497)	(0.0528)	(0.0527)	(0.0539)		(0.0545)
Doctorate		-0.8078***	-0.6050***	-0.7544***	-0.7656***		-0.7692***
		(0.0721)	(0.0762)	(0.0765)	(0.0778)		(0.0783)
M.B.A.		0.0443	-0.6490***	-0.6296***	-0.4932***		-0.4925***
		(0.1000)	(0.1418)	(0.1427)	(0.1442)		(0.1442)
M.D.		0.0224	0.4861***	0.2367	0.1830		0.1826
		(0.1308)	(0.1752)	(0.1782)	(0.1779)		(0.1779)
Black				-0.3519***	-0.4083***		-0.4104***
				(0.1086)	(0.1092)		(0.1090)
Asian				0.3626***	0.2811***		0.2794***
				(0.0605)	(0.0616)		(0.0615)
Hispanic				-0.0708	-0.2117**		-0.2124**
				(0.0959)	(0.0955)		(0.0956)
Female				-0.3411***	-0.4132***		-0.4128***
				(0.0982)	(0.0983)		(0.0983)
Age				0.2272***	0.3233***		0.3242***
				(0.0637)	(0.0651)		(0.0650)
Age squared				-0.0446***	-0.0670***		-0.0671***
				(0.0141)	(0.0144)		(0.0144)
Age cubed				0.0031***	0.0046***		0.0046***
				(0.0010)	(0.0010)		(0.0010)
Married				0.0349	0.0796		0.0802
				(0.0760)	(0.0761)		(0.0760)
Has child				-0.1247**	-0.1681***		-0.1675***
				(0.0539)	(0.0544)		(0.0544)
Female*married				-0.0353	-0.0834		-0.0830
				(0.1208)	(0.1211)		(0.1211)
Female*child				-0.1133	-0.0979		-0.0981
				(0.1102)	(0.1107)		(0.1108)
Spouse works				0.1294**	0.1333***		0.1333***
				(0.0503)	(0.0508)		(0.0508)
Survey year 1995					0.5734***		0.5731***
					(0.0853)		(0.0853)
Survey year 1997					0.4762***		0.4756***
					(0.0887)		(0.0887)
Survey year 1999					0.4606***		0.4597***
					(0.0946)		(0.0947)
Survey year 2003					1.9987***		1.9993***
					(0.0806)		(0.0806)
Survey year 2006					2.0251***		2.0254***
					(0.0799)		(0.0799)
Constant			-3.2646***	-7.0080***	-9.6707***		-9.6895***
			(0.0545)	(0.9157)	(0.9382)		(0.9378)
Includes field of highest degree?			yes	yes	yes		yes
Observations			436,441	436,441	436,441		436,441
Pseudo R-squared			0.0681	0.0910	0.111		0.111

Table 3 Panel C: Non-Science Entrepreneurship

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Immigrant	0.0527	0.0449	0.1500***	0.1852***	0.1725***		
	(0.0367)	(0.0391)	(0.0401)	(0.0494)	(0.0492)		
Immigrant highest degree in US						-0.1755***	0.1865***
						(0.0454)	(0.0538)
Immigrant highest degree NOT in US						0.3657***	0.1546**
						(0.0527)	(0.0692)
Master's degree		-0.7391***	-0.9079***	-0.9651***	-0.9882***		-0.9893***
		(0.0471)	(0.0506)	(0.0503)	(0.0505)		(0.0506)
Doctorate		-1.0129***	-1.0502***	-1.2976***	-1.2947***		-1.2959***
		(0.0698)	(0.0722)	(0.0729)	(0.0732)		(0.0734)
M.B.A.		0.6323***	1.6983***	1.6983***	1.7766***		1.7763***
		(0.0766)	(0.1615)	(0.1616)	(0.1622)		(0.1622)
M.D.		1.9415***	1.6977***	1.3921***	1.3670***		1.3671***
		(0.0490)	(0.0803)	(0.0836)	(0.0836)		(0.0836)
Black				-0.6904***	-0.7043***		-0.7052***
				(0.0743)	(0.0742)		(0.0743)
Asian				0.0002	-0.0204		-0.0185
				(0.0592)	(0.0591)		(0.0596)
Hispanic				-0.2490***	-0.2999***		-0.2999***
				(0.0693)	(0.0690)		(0.0690)
Female				-0.3270***	-0.3685***		-0.3684***
				(0.0736)	(0.0738)		(0.0738)
Age				0.1934***	0.2594***		0.2596***
				(0.0543)	(0.0552)		(0.0552)
Age squared				-0.0293**	-0.0436***		-0.0436***
				(0.0120)	(0.0122)		(0.0122)
Age cubed				0.0017**	0.0027***		0.0027***
				(0.0008)	(0.0009)		(0.0009)
Married				0.1325**	0.1681***		0.1682***
				(0.0610)	(0.0609)		(0.0609)
Has child				0.1175***	0.0915**		0.0918**
				(0.0418)	(0.0418)		(0.0418)
Female*married				0.0958	0.0764		0.0767
				(0.0875)	(0.0875)		(0.0875)
Female*child				-0.2813***	-0.2694***		-0.2692***
				(0.0764)	(0.0765)		(0.0765)
Spouse works				-0.0216	-0.0369		-0.0369
				(0.0375)	(0.0375)		(0.0375)
Survey year 1995					-0.1854***		-0.1855***
					(0.0339)		(0.0340)
Survey year 1997					-0.2046***		-0.2048***
					(0.0367)		(0.0367)
Survey year 1999					-0.2039***		-0.2043***
					(0.0394)		(0.0394)
Survey year 2003					0.3477***		0.3478***
					(0.0441)		(0.0441)
Survey year 2006					0.5589***		0.5588***
					(0.0430)		(0.0430)
Constant			-3.5748***	-7.5991***	-8.7198***		-8.7262***
			(0.0985)	(0.7868)	(0.8039)		(0.8035)
Includes field of highest degree?			yes	yes	yes		yes
Observations			436,441	436,441	436,441		436,441
Pseudo R-squared			0.0681	0.0910	0.111		0.111

Table 4: Entrepreneurship and Preferences for Self-Employment

	(1)	(2)	(3)	(4)
	All entrepreneurship		Science entrepreneurship	Non-science entrepreneurship
Immigrant	0.381***	0.345***	0.447***	0.295***
	(0.0846)	(0.0887)	(0.172)	(0.0985)
Prefer self-employment		2.278***	2.234***	2.283***
		(0.0845)	(0.170)	(0.0953)
Constant	-13.14***	-14.17***	-12.93***	-15.69***
	(1.556)	(1.646)	(2.689)	(1.916)
Observations	46,213	46,213	46,215	46,215
Mean of dependent variable	0.0110	0.0110	0.0614	0.0614
Pseudo R-squared	0.0749	0.188	0.190	0.190

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Science and Non-Science Entrepreneurship estimated together using multinomial logit.

Logit coefficients estimating exp(Dummy=1/Dummy=0)

All regressions include education level, field, race, age, gender, family structure.

Table 5 Immigrant premium and wage residuals

	(1)	(2)	(3)	(4)	(5)	(6)
	Entrepreneurship (t+1)		Science entrepreneurship (t+1)		Non-science entrepreneurship (t+1)	
Immigrant	0.3265***	0.3044***	0.4861***	0.4930***	0.2156**	0.1843**
	(0.0677)	(0.0679)	(0.0987)	(0.0998)	(0.0900)	(0.0900)
Residuals 2nd decile		-0.4612***		-0.1639		-0.5651***
		(0.1096)		(0.1895)		(0.1339)
Residuals 3rd decile		-0.5001***		-0.0382		-0.6973***
		(0.1083)		(0.1832)		(0.1381)
Residuals 4th decile		-0.4610***		-0.0377		-0.6455***
		(0.1082)		(0.1882)		(0.1354)
Residuals 5th decile		-0.3417***		0.0251		-0.5030***
		(0.1111)		(0.1782)		(0.1449)
Residuals 6th decile		-0.2993***		0.2355		-0.5772***
		(0.1097)		(0.1814)		(0.1457)
Residuals 7th decile		-0.2851***		0.1012		-0.4724***
		(0.1090)		(0.1887)		(0.1341)
Residuals 8th decile		-0.1387		0.1109		-0.2434*
		(0.1059)		(0.1744)		(0.1336)
Residuals 9th decile		-0.0075		0.2327		-0.1131
		(0.1017)		(0.1831)		(0.1221)
Residuals 10th decile		0.7484***		0.5924***		0.7265***
		(0.0905)		(0.1929)		(0.1017)
Observations	214,827	214,827	214,827	214,827	214,827	214,827
Pseudo R square	0.091	0.108	0.109	0.126	0.109	0.126

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Science and Non-Science Entrepreneurship estimated together using multinomial logit.

Logit coefficients estimating exp(Dummy=1/Dummy=0)
All regressions include education level, field, gender, race, age, family structure, survey year.
Sample: 1997 NSCG and NSRCG respondents who were interviewed again in 1999.

Table 6: Entrepreneurship and wage residuals for natives and immigrants

	(1) Entrepreneurship (t+1)	(2) Science entrepreneurship (t+1)	(3) Non-science entrepreneurship (t+1)
Residuals 2nd decile*native	-0.5553***	-0.2619	-0.6449***
	(0.1307)	(0.2358)	(0.1585)
Residuals 3rd decile*native	-0.5372***	-0.1216	-0.6870***
	(0.1242)	(0.2259)	(0.1537)
Residuals 4th decile*native	-0.5639***	-0.2543	-0.6654***
	(0.1271)	(0.2385)	(0.1529)
Residuals 5th decile*native	-0.4299***	-0.1616	-0.5164***
	(0.1301)	(0.2241)	(0.1628)
Residuals 6th decile*native	-0.3753***	0.1014	-0.5812***
	(0.1257)	(0.2216)	(0.1623)
Residuals 7th decile*native	-0.3402***	-0.0026	-0.4717***
	(0.1265)	(0.2374)	(0.1501)
Residuals 8th decile*native	-0.1855	0.0199	-0.2502*
	(0.1217)	(0.2159)	(0.1495)
Residuals 9th decile*native	-0.0594	0.1314	-0.1229
	(0.1162)	(0.2222)	(0.1372)
Residuals 10th decile*native	0.7509***	0.5211**	0.7577***
	(0.1030)	(0.2340)	(0.1146)
Residuals 1st decile*immigrant	0.1383	0.1568	0.1892
	(0.1536)	(0.2671)	(0.1853)
Residuals 2nd decile*immigrant	0.0133	0.2070	0.0000
	(0.1623)	(0.2807)	(0.1985)
Residuals 3rd decile*immigrant	-0.2548	0.2758	-0.5767**
	(0.1843)	(0.2697)	(0.2780)
Residuals 4th decile*immigrant	0.0824	0.6551**	-0.3253
	(0.1692)	(0.2684)	(0.2399)
Residuals 5th decile*immigrant	0.1468	0.6407**	-0.2179
	(0.1695)	(0.2548)	(0.2623)
Residuals 6th decile*immigrant	0.1397	0.7128**	-0.3576
	(0.1944)	(0.2798)	(0.2945)
Residuals 7th decile*immigrant	0.0551	0.4841*	-0.2864
	(0.1752)	(0.2862)	(0.2253)
Residuals 8th decile*immigrant	0.1573	0.4475*	-0.0044
	(0.1702)	(0.2389)	(0.2526)
Residuals 9th decile*immigrant	0.3151*	0.6048**	0.1483
	(0.1711)	(0.2978)	(0.2073)
Residuals 10th decile*immigrant	0.6618***	0.8142***	0.6204***
	(0.1433)	(0.2977)	(0.1619)
Observations	214,827	214,827	214,827
Pseudo R square	0.109	0.127	0.127

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Science and Non-Science Entrepreneurship estimated together using multinomial logit.
Logit coefficients estimating exp(Dummy=1/Dummy=0)
All regressions include education level, field, gender, race, age, family structure, survey year.

Table 6A Test for the existence of the immigrant premium at each decile (test of b(Residual i*native) = b(Residual i*immigrant)

Test b(Residual i*native = Residual i*immigrant)	(1) Entrepreneurship (t+1)	(2) Science Entrepreneurship (t+1)	(3) Non-science Entrepreneurship (t+1)
i=1	n.s.	n.s.	n.s.
i=2	***	*	***
i=3	n.s.	n.s.	n.s.
i=4	***	***	n.s.
i=5	***	***	n.s.
i=6	***.	***	n.s.
i=7	**	*	n.s.
i=8	**	**	n.s.
i=9	**	*	n.s.
i=10	n.s.	n.s.	n.s.
Observations	149,754	149,754	149,754
Pseudo R square	0.116	0.116	0.140

n.s. not significant. *Statistically significant at the 10% level, ** 5% level, *** 1% level

Table 7 Robustness check Entrepreneurship and wages in paid job

	Entrepreneurship (t+1)	Science entrepreneurship (t+1)	Non-science entrepreneurship (t+1)
Wages 2nd decile*native	-0.5282***	-0.5408*	-0.5113***
	(0.1370)	(0.3146)	(0.1522)
Wages 3rd decile*native	-0.4901***	-0.2765	-0.5300***
	(0.1379)	(0.2822)	(0.1599)
Wages 4th decile*native	-0.6357***	-0.4137	-0.6923***
	(0.1409)	(0.2659)	(0.1710)
Wages 5th decile*native	-0.5119***	0.0200	-0.7318***
	(0.1385)	(0.2681)	(0.1735)
Wages 6th decile*native	-0.3706***	-0.1985	-0.4168**
	(0.1392)	(0.2793)	(0.1662)
Wages 7th decile*native	-0.2006	-0.0175	-0.2502
	(0.1422)	(0.2580)	(0.1778)
Wages 8th decile*native	-0.1502	0.0558	-0.2234
	(0.1320)	(0.2653)	(0.1584)
Wages 9th decile*native	0.0839	0.2301	0.0304
	(0.1427)	(0.2672)	(0.1766)
Wages 10th decile*native	0.6626***	0.3020	0.7337***
	(0.1238)	(0.2848)	(0.1392)
Wages 1st decile*immigrant	0.2749	-0.2236	0.4498**
	(0.1942)	(0.4155)	(0.2167)
Wages 2nd decile*immigrant	0.0840	0.3540	0.0354
	(0.2113)	(0.3717)	(0.2659)
Wages 3rd decile*immigrant	-0.1832	0.4639	-0.5107*
	(0.2121)	(0.3438)	(0.2823)
Wages 4th decile*immigrant	0.1179	0.5959*	-0.1086
	(0.1764)	(0.3132)	(0.2234)
Wages 5th decile*immigrant	-0.1766	-0.0736	-0.1653
	(0.2008)	(0.3203)	(0.2634)
Wages 6th decile*immigrant	0.2337	0.7169**	-0.1401
	(0.1885)	(0.2983)	(0.2912)
Wages 7th decile*immigrant	0.0421	0.5494*	-0.5213**
	(0.1969)	(0.3172)	(0.2394)
Wages 8th decile*immigrant	0.3254*	0.6174**	0.0226
	(0.1725)	(0.3020)	(0.2418)
Wages 9th decile*immigrant	0.2698	0.6577**	-0.1868
	(0.1692)	(0.2946)	(0.2480)
Wages 10th decile*immigrant	0.6985***	0.5212*	0.7818***
	(0.1493)	(0.3049)	(0.1722)
Observations	214,827	214,827	214,827
Pseudo R square	0.106	0.124	0.124

Table 8 Entrepreneurship and wage residuals for natives, immigrant by whether highest degree in US

	Entrepreneurship	Science entrep.	Non-science entrep.
Residuals 2nd decile*native	-0.5554***	-0.2624	-0.6450***
	(0.1307)	(0.2358)	(0.1585)
Residuals 3rd decile*native	-0.5376***	-0.1228	-0.6871***
	(0.1242)	(0.2259)	(0.1537)
Residuals 4th decile*native	-0.5642***	-0.2555	-0.6655***
	(0.1270)	(0.2385)	(0.1529)
Residuals 5th decile*native	-0.4303***	-0.1631	-0.5165***
	(0.1301)	(0.2241)	(0.1628)
Residuals 6th decile*native	-0.3757***	0.1001	-0.5813***
	(0.1257)	(0.2216)	(0.1623)
Residuals 7th decile*native	-0.3406***	-0.0043	-0.4718***
	(0.1265)	(0.2373)	(0.1502)
Residuals 8th decile*native	-0.1858	0.0186	-0.2502*
	(0.1217)	(0.2159)	(0.1496)
Residuals 9th decile*native	-0.0597	0.1302	-0.1230
	(0.1162)	(0.2222)	(0.1372)
Residuals 10th decile*native	0.7511***	0.5209**	0.7579***
	(0.1030)	(0.2340)	(0.1146)
Residuals 1st decile*highest degree US	0.1976	0.0530	0.3152
	(0.2059)	(0.3158)	(0.2476)
Residuals 2nd decile*highest degree US	0.0254	0.1529	0.0448
	(0.2017)	(0.3475)	(0.2456)
Residuals 3rd decile*highest degree US	-0.2266	0.2027	-0.4609
	(0.2180)	(0.3214)	(0.3161)
Residuals 4th decile*highest degree US	-0.0688	0.4273	-0.3959
	(0.1990)	(0.2959)	(0.2896)
Residuals 5th decile*highest degree US	-0.0777	0.4510	-0.5616*
	(0.1944)	(0.2851)	(0.3181)
Residuals 6th decile*highest degree US	0.1063	0.4360*	-0.0909
	(0.2068)	(0.2629)	(0.3326)
Residuals 7th decile*highest degree US	0.0046	0.4458	-0.3906
	(0.2113)	(0.3219)	(0.2931)
Residuals 8th decile*highest degree US	0.1848	0.5116**	-0.0307
	(0.1899)	(0.2508)	(0.2983)
Residuals 9th decile*highest degree US	0.2510	0.6819**	-0.0671
	(0.2092)	(0.3453)	(0.2542)
Residuals 10th decile*highest degree US	0.8217***	1.0659***	0.7418***
	(0.1610)	(0.3002)	(0.1863)
Residuals 1st decile*highest degree abroad	0.1126	0.2032	0.1305
	(0.1835)	(0.3109)	(0.2236)
Residuals 2nd decile*highest degree abroad	0.0003	0.2644	-0.0501
	(0.2219)	(0.3558)	(0.2775)
Residuals 3rd decile*highest degree abroad	-0.2985	0.3856	-0.7607
	(0.2828)	(0.3465)	(0.4837)
Residuals 4th decile*highest degree abroad	0.2998	0.9804***	-0.2232
	(0.2519)	(0.3632)	(0.3727)
Residuals 5th decile*highest degree abroad	0.4416*	0.9400***	0.1346
	(0.2513)	(0.3363)	(0.3749)
Residuals 6th decile*highest degree abroad	0.1971	1.1021**	-1.0521**
	(0.3589)	(0.4323)	(0.4933)
Residuals 7th decile*highest degree abroad	0.1558	0.5632	-0.1106
	(0.2512)	(0.4097)	(0.2976)
Residuals 8th decile*highest degree abroad	0.0903	0.2519	0.0420
	(0.2867)	(0.3718)	(0.4014)
Residuals 9th decile*highest degree abroad	0.4282*	0.4250	0.4665
	(0.2486)	(0.4030)	(0.3082)
Residuals 10th decile*highest degree abroad	0.3632	0.2728	0.4001*
	(0.2232)	(0.5055)	(0.2378)
Observations	214,827	214,827	214,827
Pseudo R square	0.109	0.127	0.127

Figure 1a

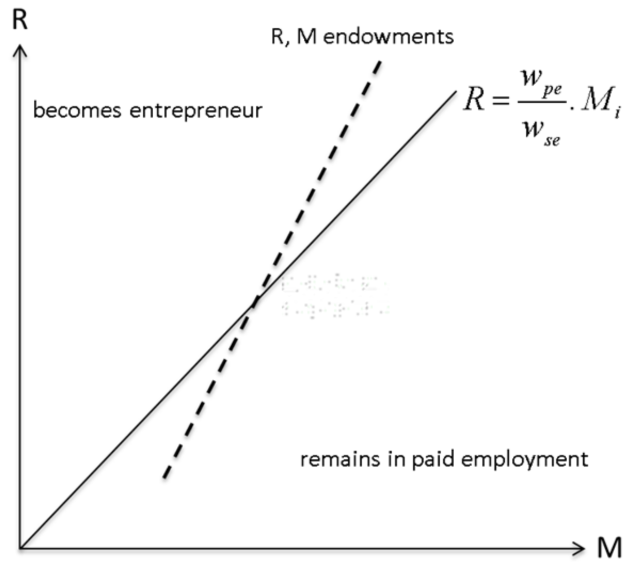


Figure 1b

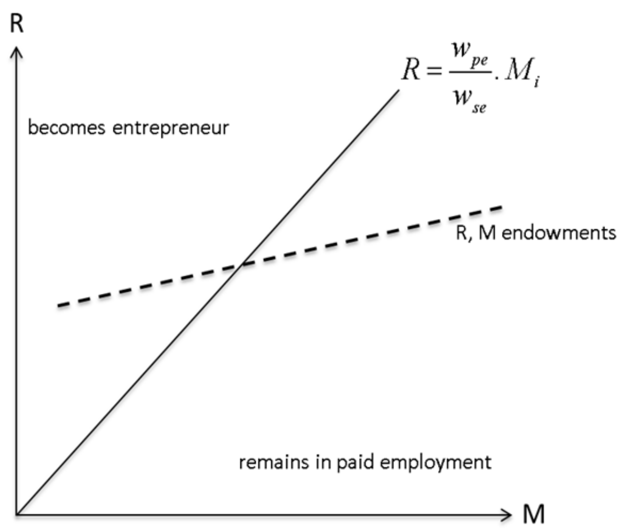


Figure 1c

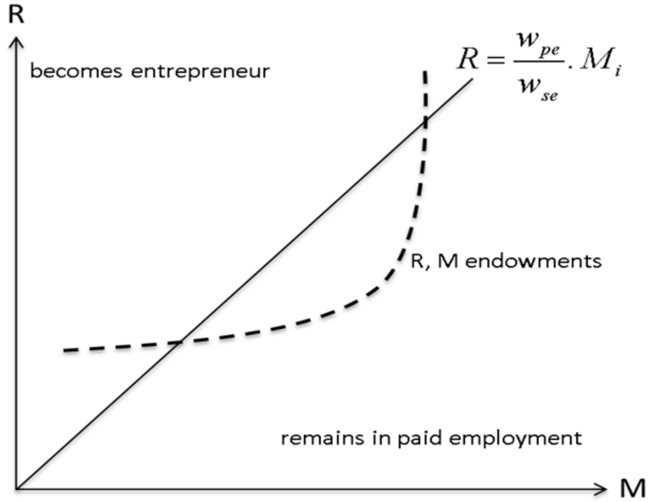


Figure 1d

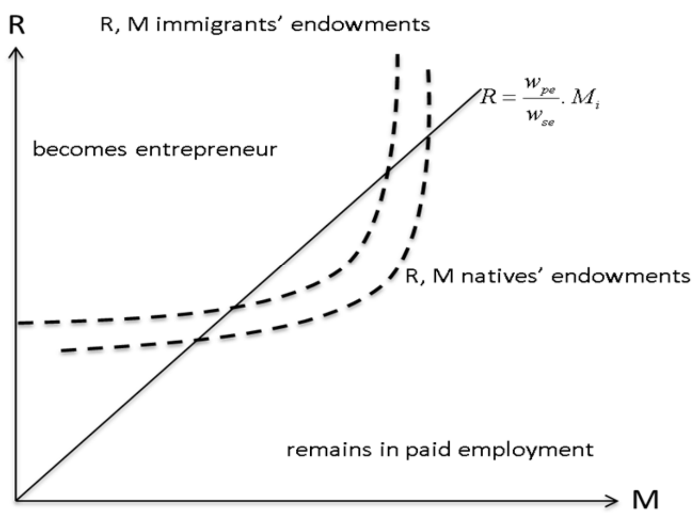


Figure 1e

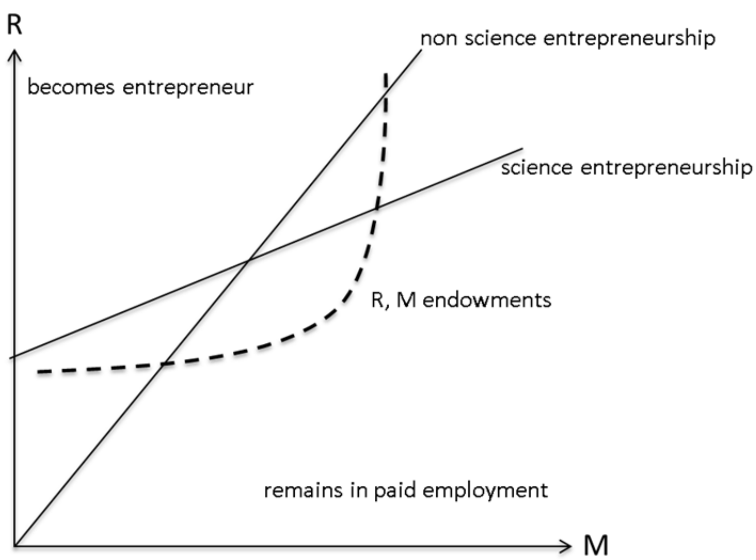


Figure 2: Distribution by Wage Residual Deciles and Immigrant Status (2-year sample)

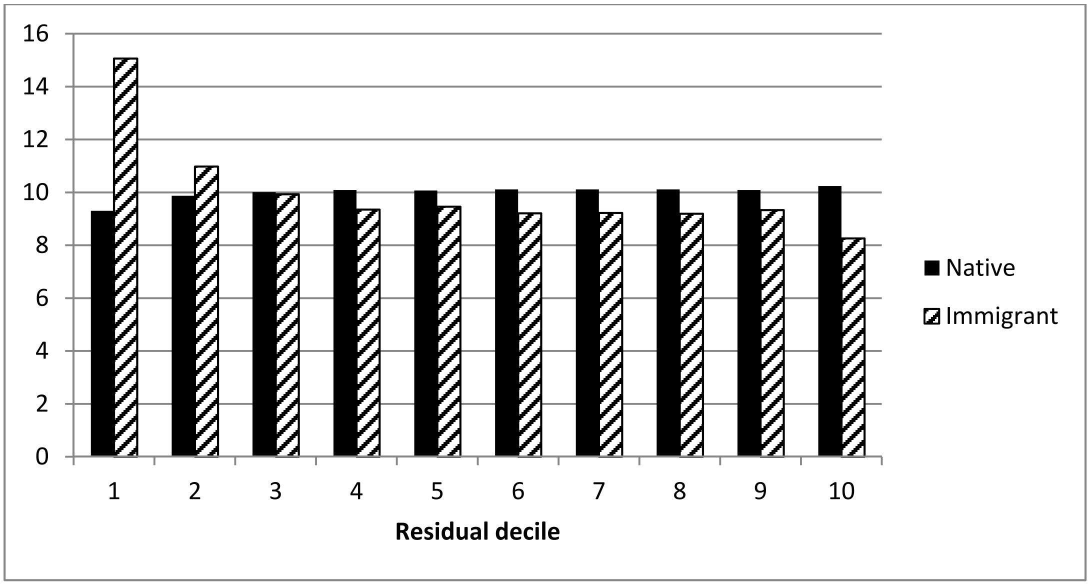


Figure 3: Distribution by Wage Residual Deciles and Immigrant Education Location (2-year sample)

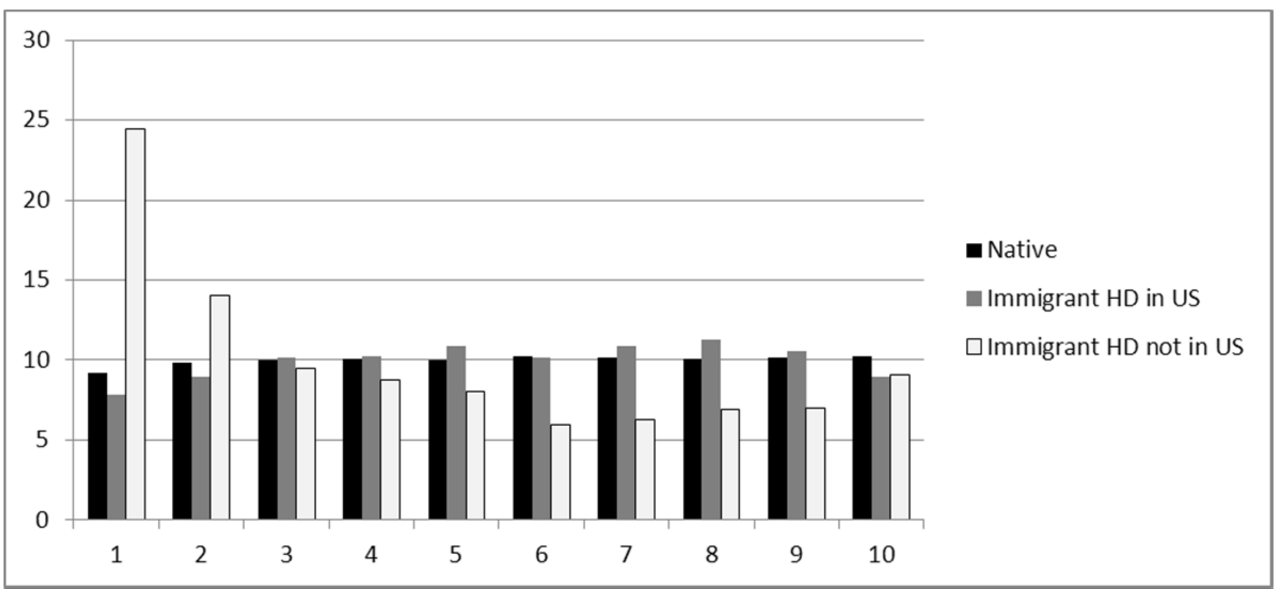


Figure 4

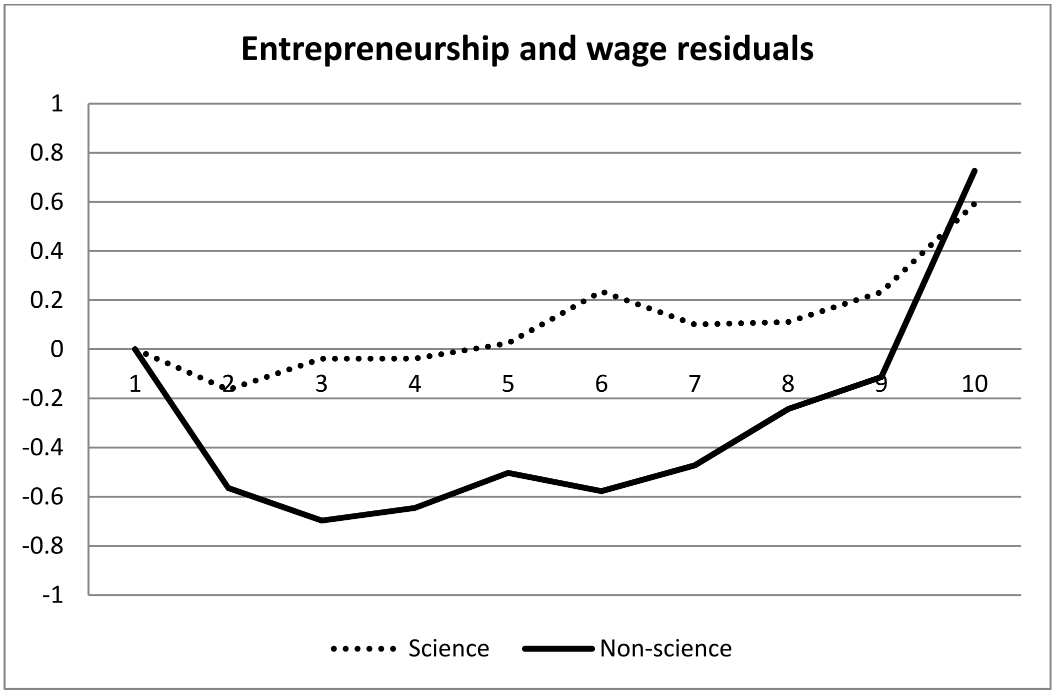
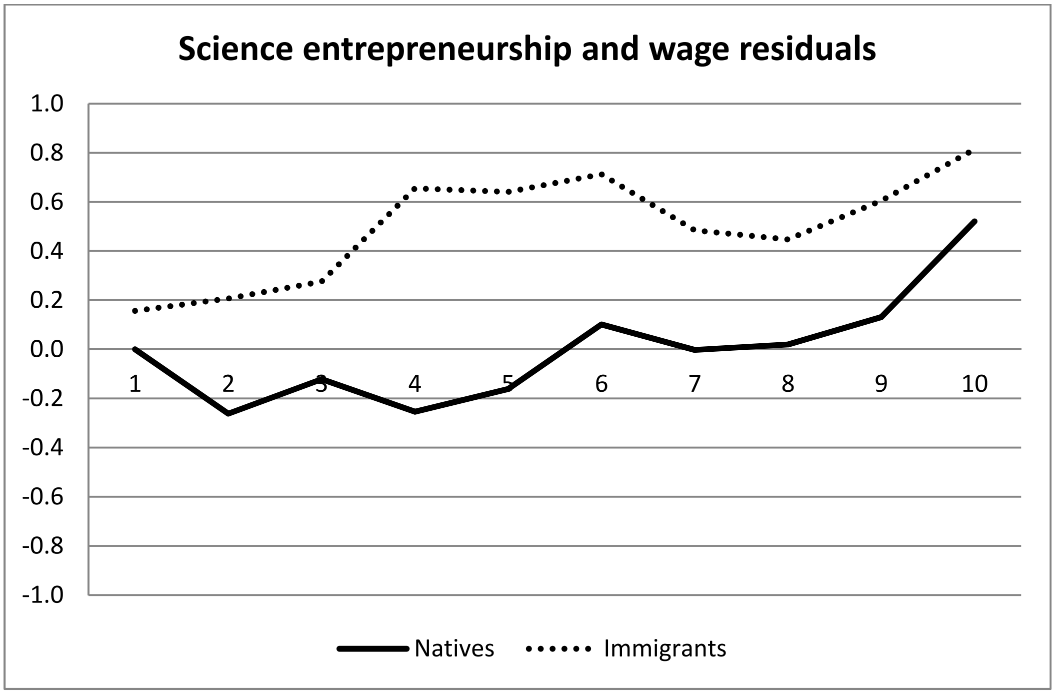
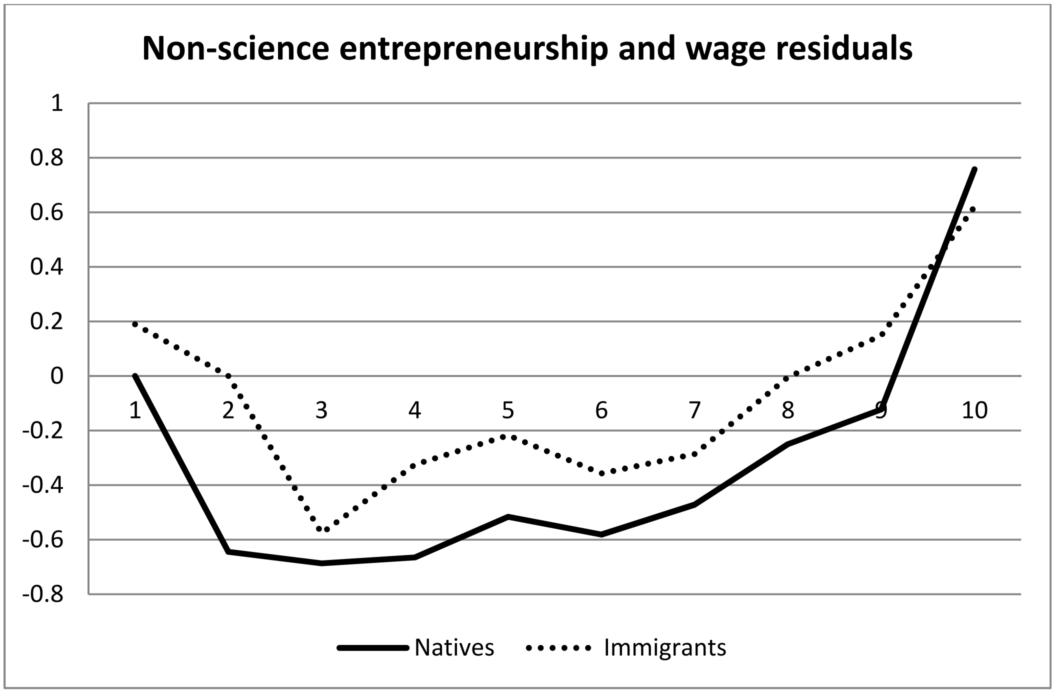

Entrepreneurship and wage residuals
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
1
2
3
4
5
6
7
8
9
10
Science
Non-science

Figure 5

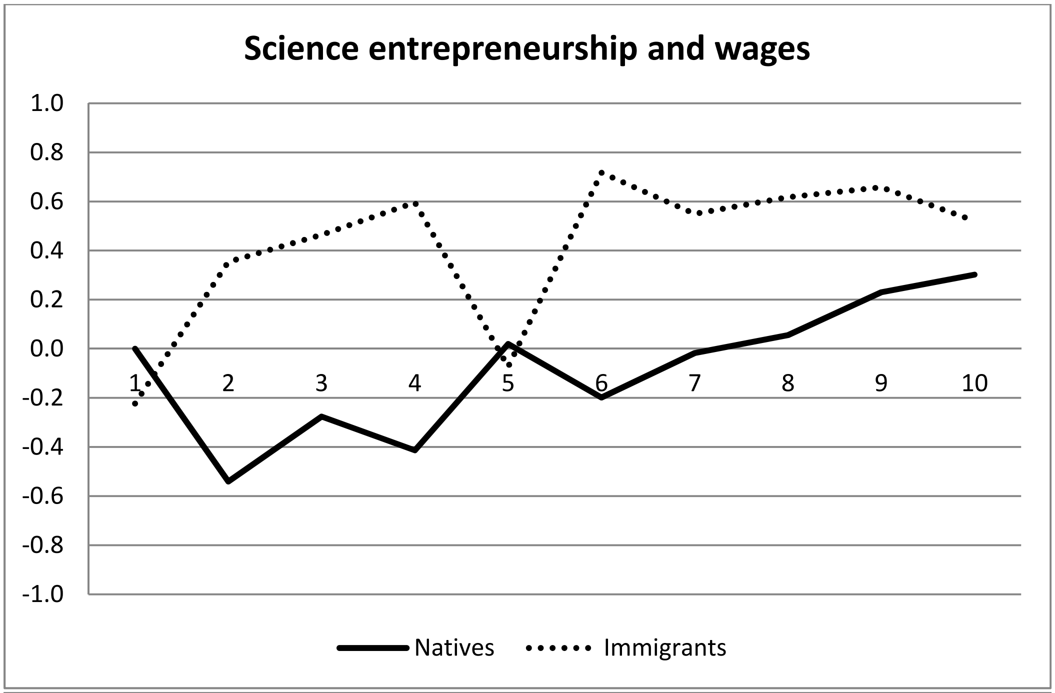


Science entrepreneurship and wage residuals
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1
2
3
4
5
6
7
8
9
10
Natives
Immigrants



Non-science entrepreneurship and wage residuals
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
1
2
3
4
5
6
7
8
9
10
Natives
Immigrants

Figure 6


Science entrepreneurship and wages
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1
2
3
4
5
6
7
8
9
10
Natives
Immigrants

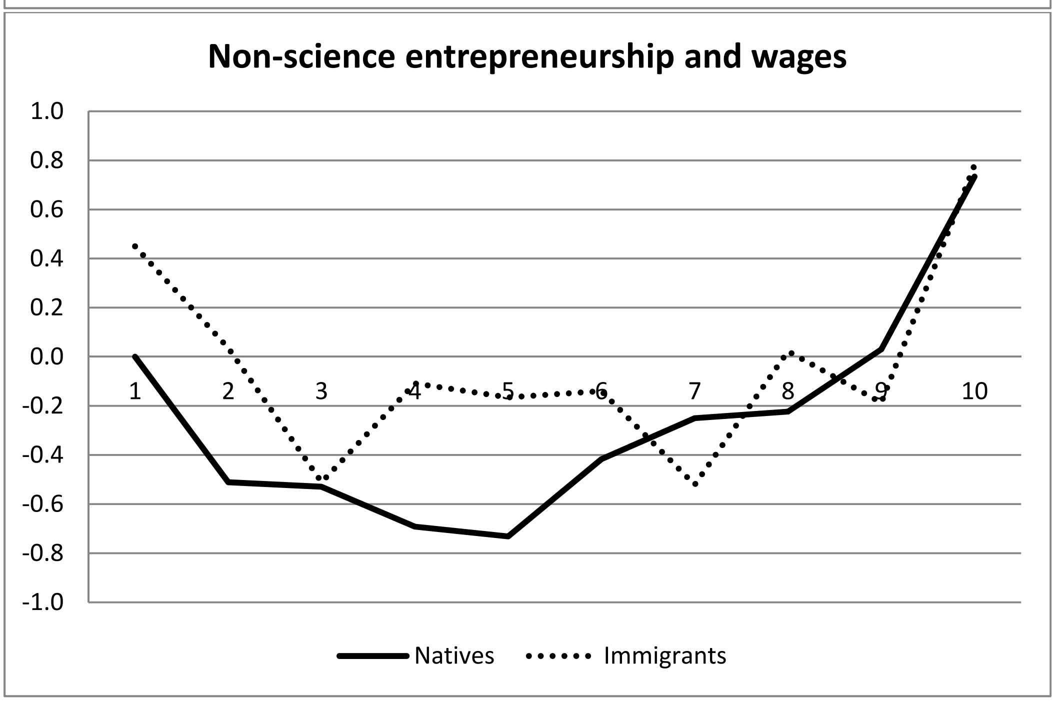
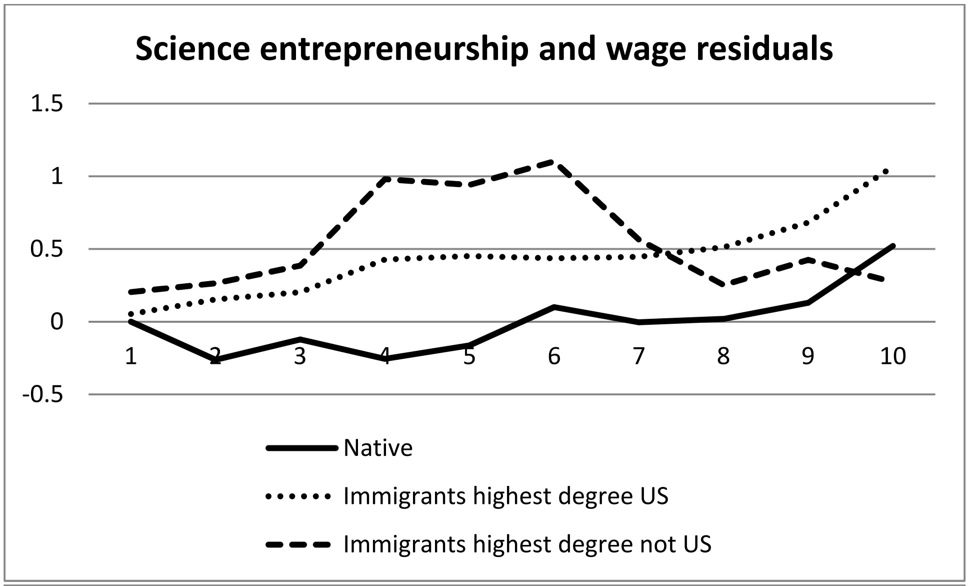
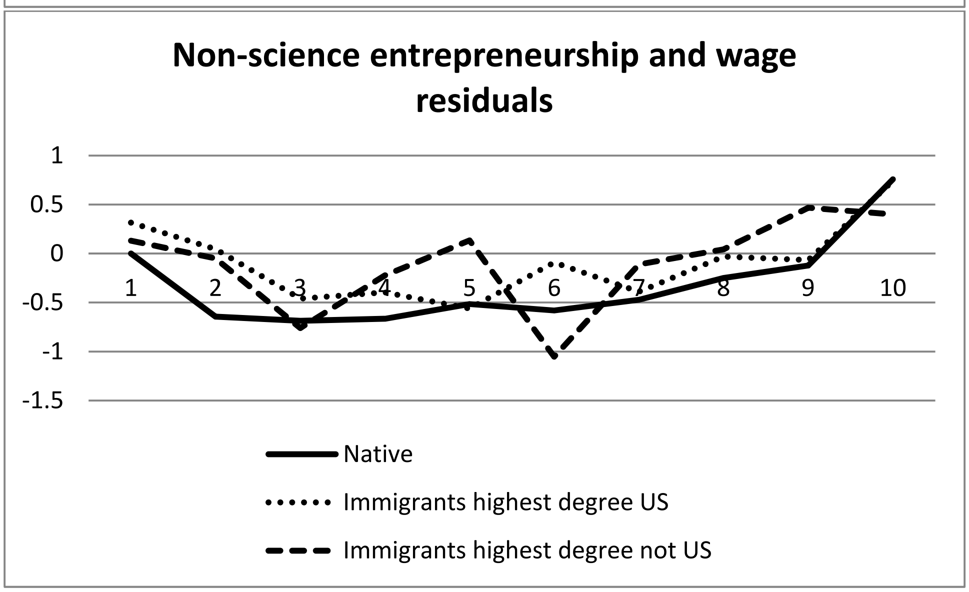

Non-science entrepreneurship and wages
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1
2
3
4
5
6
7
8
9
10
Natives
Immigrants

Figure 7


Science entrepreneurship and wage residuals
1.5
1
0.5
0
-0.5
1
2
3
4
5
6
7
8
9
10
Native
Immigrants highest degree US
Immigrants highest degree not US


Non-science entrepreneurship and wage residuals
1
0.5
0
-0.5
-1
-1.5
1
2
3
4
5
6
7
8
9
10
Native
Immigrants highest degree US
Immigrants highest degree not US

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 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 primary work activity is not professional services.
- The individual has a job as a manager and his primary work activity is research (Design of Equipment, Processes, Development, Computer Applications, Programming, Basic research, Applied Research); the individual is a manager and his 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 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 his primary work activity is not 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 primary work activity is professional services.