

Differences between Men and Women in Self-Employment Outcomes: The Role of Skills and Preferences for Business Professionals ^{*}

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Abstract

We study self-employment among highly educated, career-oriented business professionals using panel data from prospective graduate management students. Analyzing men and women separately, we assess how cognitive ability, non-cognitive traits, and balanced skills shape self-employment outcomes. For women, non-cognitive traits and balanced skills predict entry. For men, preferences related to work-life balance and job characteristics are more influential. In traditional employment, similar traits raise earnings for both groups. In self-employment, however, returns diverge: women gain more from quantitative skills, while men benefit from balanced non-cognitive traits. Notably, the traits driving entry differ from those linked to later financial success.

JEL Classification: D91, J16, J24, J31, L26.

Keywords: Self-employment; Non-cognitive skills; Skill balance; Differences between men and women.

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Introduction

Despite gains in education and workforce involvement, women continue to have limited participation in high-status business roles, raising important questions about the factors that shape career decisions and advancement. Of the 2,640 billionaires listed globally, only 13% are women, and less than 30% of these women are self-made, meaning that they either started their company as founders or co-founders, or established their own fortune as opposed to inheriting it (Peterson-Withorn, 2024). These patterns mirror labor market trends, where women are less likely to be self-employed or work in high-paying business and financial occupations (Bureau of Labor Statistics, 2024).

Various explanations have been proposed to account for these differences. One line of research attributes women's lower participation in self-employment and leadership to behavioral traits, such as risk aversion, lower confidence, reduced competitiveness, or weaker bargaining preferences (Bertrand et al., 2010; Azmat and Petrongolo, 2014; Croson and Gneezy, 2009). However, much of the evidence on these traits is based on laboratory or survey experiments, and their applicability to actual career decisions is not always clear. Additionally, the effect of these traits may be mediated by contextual factors such as occupational constraints, family responsibilities, or labor force attachment.

Comparing self-employment patterns among men and women is further complicated by selection. Women in representative samples often include individuals with weaker attachment to the labor force, who may pursue self-employment for reasons unrelated to business ambition—such as flexibility or family compatibility (Hundley, 2000; Georgellis and Wall, 2005; Gurley-Calvez et al., 2009; Leoni and Falk, 2010; Özcan, 2011). As a result, it can be difficult to distinguish between these women's preferences and constraints. There is a need for research that focuses on men and women with similar levels of ambition and career commitment.

This study addresses that gap by using data from the Graduate Management Admission Test (GMAT) Registrant Survey—a panel dataset of individuals who registered to take the GMAT, which was required for admission to most graduate business programs. Our sample includes over 3,400 career-motivated men and women who are relatively homogeneous in their business aspirations, prior investments in human capital, and intent to pursue demanding professional paths. By focusing on this group, we can assess the differences in self-employment outcomes between men and women while holding constant many of the confounding factors that typically complicate such comparisons.

We examine the relationship between self-employment and a rich set of pre-determined characteristics: cognitive skills (verbal and quantitative), non-cognitive traits relevant to

business success, and preferences over work-life balance and job-related attributes. We also construct measures of “skill balance”—a concept drawn from Lazear’s Jack-of-all-trades theory—capturing the extent to which individuals are broadly rather than narrowly skilled (Lazear, 2004, 2005). This approach allows us to explore whether the factors associated with self-employment differ between men and women, and whether the traits influencing entry into self-employment are also linked to earnings and success.

Background

This paper contributes to several strands of literature on the determinants of self-employment. Existing studies have explored the role of cognitive skills, non-cognitive traits, skill balance, and preferences in shaping both the likelihood of self-employment and entrepreneurial success. Much of this literature relies on large-scale, nationally representative longitudinal surveys such as the National Educational Longitudinal Study (NELS) or the National Longitudinal Survey of Youth (NLSY) (Eren and Sula, 2012; Hartog et al., 2010; Levine and Rubinstein, 2017), which include a broad cross-section of individuals, many of whom have only marginal attachment to the labor market. Because subsamples of women often include part-time or intermittently employed individuals, these studies are limited in their ability to isolate patterns specific to men and women.

Other papers use data from military enlistment exams or compulsory assessments, such as those used in Sweden or Finland, to proxy for innate traits like cognitive ability, leadership, or emotional stability (Uusitalo, 2001; Humphries, 2017; Aldén et al., 2017). While these data provide useful variation, they often exclude women or do not report results separately for men and women. Even when both groups are included, the analysis typically does not investigate whether cognitive or non-cognitive traits relate differently to outcomes across groups. For instance, Hartog et al. (2010) include women but only allow for level effects, and Aldén et al. (2017) exclude women altogether.

Our study departs from this literature by focusing on a more selective sample of aspiring business professionals, with a more balanced distribution of men and women. This allows for direct and symmetric comparisons across groups. We jointly consider a broader range of predictors—cognitive and non-cognitive skills, skill balance, and preferences—within a single framework. This enables us to evaluate the relative importance of skills and tastes in shaping both entry into and performance in self-employment.

We also contribute to the literature testing Lazear’s Jack-of-all-trades theory, which posits that entrepreneurs need a balanced portfolio of skills rather than deep specializa-

tion. Prior empirical tests have shown mixed results. Hartog et al. (2010) and Aldén et al. (2017) evaluate the role of skill balance in both entry and earnings, finding partial support for the theory. However, neither study investigates whether these effects vary between men and women. Patel and Ganzach (2019) focus exclusively on cognitive skill balance and find that it increases earnings but not self-employment entry. Tegtmeier et al. (2016) analyze German women using both innate and acquired skill measures, but rely on cross-sectional data and omit cognitive ability and preference measures.

Moreover, our panel dataset allows us to address concerns of reverse causality—namely, that observed skills or preferences may reflect outcomes rather than precede them. Because we observe most predictors prior to any realization of self-employment or earnings, we reduce bias from post-hoc rationalization or changes in self-concept.

Finally, we connect to a line of research exploring non-pecuniary motivations for entrepreneurship. Prior work finds that many individuals—especially women—pursue self-employment for flexibility, autonomy, or family compatibility rather than financial gain (Benz and Frey, 2008; Hyytinen et al., 2013; Hurst and Pugsley, 2011; Burke et al., 2002). These studies suggest that job satisfaction and personal alignment matter at least as much as monetary returns. Our findings for men are consistent with this literature: men who prioritize autonomy or personal interest are more likely to select into self-employment. However, we find no such patterns for women in our sample, highlighting the importance of analyzing men and women separately within a more homogeneous career-oriented population.

Materials and Methods

In this section, we first describe the data, the outcome variables of interest, the explanatory variables of interest, and the controls used for this study. Next, we provide descriptive statistics of our sample, and describe our empirical methodology.

Data

Our study uses data from the GMAT Registrant Survey, a national random sample of individuals who registered to take the GMAT. The GMAT, sponsored by the Graduate Management Admission Council (GMAC), has traditionally been a requirement for application to the majority of MBA and other graduate business programs in the United States.¹

The longitudinal survey was conducted in four waves between 1990 and 1998. The first wave of the survey was collected in 1990. Three follow-up surveys were mailed to the same individuals from 1991 to 1998. All individuals were sent the follow-up survey regardless of whether or not they ultimately took the GMAT, and regardless of their MBA enrollment or completion. The survey contains comprehensive details on individuals' employment status, job characteristics and earnings, work experience, family background, and educational attainment. Initially, 5,885 individuals responded the survey. This number declined to 3,771 by the fourth and final wave in 1998.

Our analysis utilizes data from all four survey waves. We restrict the sample of all participants who completed the survey to those participants who took the GMAT, since we include GMAT scores as measures of cognitive ability. We restrict attention to individuals, who, during a given wave, reported working for 35 hours or more per week, including both self-employed individuals and individuals working for paid employment. After dropping individuals with missing values for any of our variables of interest, our sample includes 1,456 women and 2,072 men from the first survey wave.

Outcome Variables

There are two main outcome variables in this study. The first one is an indicator for whether or not an individual has ever held self-employment after the first survey wave, also referred to as "ever self-employed", and the second one is earnings.

Eventual Self-employment

To construct our ever self-employed variable of interest, we consider whether or not an individual in our sample was engaged in self-employment in at least one of the later waves of the survey. Information on self-employment is gathered from waves II, III, and IV, occurring approximately 16 months, 3.6 years, and 7.2 years after wave I, respectively. We exclude part-time self-employment that involves an insubstantial number of hours, though we do not rule out the possibility that those individuals may simultaneously hold employment elsewhere.

For a given wave, we define an individual to be self-employed if two conditions hold: the individual reported self-employment as their current job, and the individual reported working at least 35 hours per week at that job.² Our ever self-employed binary variable is equal to one for an individual who experiences self-employment in at least one wave among wave II, wave III, and wave IV. Self-employment is equal to zero for individuals who were not self-employed in any of the three waves that the survey was administered.

This way of defining self-employed is similar to that in Hartog et al. (2010), Table IV, panel B. This can be thought of as identifying entrepreneurial “types” as individuals who are willing to be self-employed, even if they hold traditional employment in a different wave. The reason we prefer this to a panel specification is that a panel would place more weight on individuals who are self-employed in more than one wave compared to those who are self-employed in fewer waves. That is, using a panel specification conflates being an entrepreneurial “type” with being persistent and/or successful in self-employment. Given that startups are highly likely to fail, and given that promising entrepreneurial ventures may still fail due to other factors, such as inadequacy of resource providers (i.e., capital or inputs for production) or industry-specific characteristics, individuals who survive in self-employment should not receive more emphasis when studying the correlates of entrepreneurial types.³

Earnings

Our second outcome of interest is reported earnings from an individual’s primary job in each wave II, III, and IV. For this case, we only consider individuals who reported their jobs as being current in each individual wave. As with self-employment outcomes, we restrict the sample to only those working at least 35 hours per week for both self-employed and traditionally employed individuals. Since the same individuals who are in traditional employment in one or more waves may be self-employed in other waves, we use a panel structure for this exercise.

We specify our earnings variable as the logarithm of salary. In these calculations, all bonuses, commissions and tips, except one-time starting bonuses are included.⁴

Some individuals report full-time employment, but do not report earnings. While those individuals are considered for the ever self-employed indicator, those observations are dropped for the earnings analysis. After dropping observations that do not have GMAT scores or that are missing any of our explanatory variables of interest, we obtain 4,239 men, and 2,937 women.

Explanatory Variables

Our explanatory variables of interest are derived from wave I of the GMAT Registrant Survey. They can be split into the following categories: (1) Cognitive Skills; (2) Non-cognitive traits deemed important for business; (3) Skill balance indicators; (4) Work/life balance preferences; and (5) Job-related preferences.

Cognitive Skills

For cognitive skills, we use actual GMAT scores on both the quantitative and the verbal sections of the test. These official scores are linked from official testing records to the survey data.

Business-related non-cognitive traits

For non-cognitive skills and characteristics, we use responses obtained in wave I for participant self-assessment in skills and characteristics that are potentially important as a manager or executive. The survey questions ask respondents to “indicate the extent to which you think you have each of these 16 characteristics or skills,” with responses ranging from 1 (“not at all” having the characteristic or skill) to 4 (“very much” having the characteristic or skill).

From these questions, we identify the following nine non-cognitive or “soft” skills: communication skills, ability to work with people from diverse backgrounds, ability to organize, ability to capitalize on change, ability to delegate tasks, ability to adapt theory to practical situations, understanding business in other cultures, ability to motivate others, and being a team player. In addition to these skills, we include five individual traits (good intuition, initiative, assertiveness, high ethical standards, and shrewdness) and two factors (physical attractiveness and knowing the right people) that may contribute to professional success.

Our main specification uses principal component analysis separately for men and for women to determine a single index of non-cognitive ability. We take only the first component, as it explains most of the variance. We also conduct our analyses considering separate non-cognitive traits.

This strategy of using self reports of non-cognitive traits follows Bandura (1977)’s theory positing that people’s behavior is more heavily influenced by their beliefs regarding their capabilities rather than their actual capacity to achieve something.⁵ There is evidence that this is relevant for decisions to become an entrepreneur (Eren and Sula, 2012; Arenius and Minniti, 2005; Hamilton et al., 2019) as well as for success in start-up survival and earnings (Caliendo et al., 2023; Hamilton et al., 2019). In this sense, self assessment in these characteristics can be interpreted as measurements of business confidence. Prior research has used these variables in the context of estimating the earnings gap between men and women and evaluating job market outcomes (Grove et al., 2011; Chen et al., 2017).⁶

Skill Balance Indicators

To explore the role of skill balance in self employment outcomes and performance and test Lazear's Jack-of-all-trades theory, we construct a measure of skill balance based on GMAT scores and self-assessed non-cognitive traits. As in Hartog et al. (2010) and Aldén et al. (2017), we use the coefficient of variation of individual scores (CV_i), defined as the standard deviation of the measures of the skills in question for the same individual i , divided by their mean. This coefficient of variation is multiplied by negative one to facilitate interpretation as in Aldén et al. (2017), so higher values are closer to zero and correspond to a more balanced skill set.

We construct two measures of skill balance. The first measure includes only cognitive skills, as given by the scores in the quantitative component and the verbal component of the GMAT. The second measure includes only self-assessment of all non-cognitive traits. These are referred to as "cognitive skill balance" and "non-cognitive skill balance," respectively.

Work-life balance preferences

Preferences over family versus career have been shown to affect self-employment decisions particularly for women (Gurley-Calvez et al., 2009; Tegtmeier et al., 2016). Because our analysis examines men and women separately, we account for potential differences in broader life priorities by including indicator variables for whether individuals report that family, career, and wealth are "very important"

Job-related preferences

There is evidence suggesting that non-pecuniary benefits affect decisions to become self-employed Hamilton (2000); Benz and Frey (2008); Blanchflower and Oswald (1998); Hyytinen et al. (2013); Hurst and Pugsley (2011). As with the previous category, the role of job-related preferences may vary across individuals and may have different effects on men's and women's decisions to pursue self-employment. To address this possibility, we include variables that represent the importance of certain job attributes for participants' expected future position (i.e., 5 years later).

As with preferences over work-life balance, we create binary variables indicating whether individuals felt, at the time of wave I, that the following job characteristics were "very important" for a future job: "The work is interesting," "I have enough authority to do my job," "The job security is good," "The pay is good," "The problems I am expected to solve are hard enough," "I am free from the conflicting demands that others make of me," and "The hours are good."

Controls

Given the extensive evidence on the determinants of self-employment, we include the following classes of control variables derived from wave I of the GMAT Registrant Survey: (1) Demographic characteristics; (2) Family background variables; (3) Academic background variables; and (4) Professional background variables. For the earnings panel, we additionally include later-life events.

Demographic characteristics

We include the respondent's age at the time of the wave I survey, indicator variables for race/ethnicity (Asian, Black, and Hispanic). We also include indicator variables for whether or not the individual was married or co-habiting in wave I, and for whether or not they had any children under 18 living at home at least half of the time.

Family background variables

This category includes the number of years of education attained by the respondent's father and mother. Parents' education can be considered as a proxy for wealth, which is known to increase the probability of becoming self-employed.⁷

Academic background

We include undergraduate grade point average (out of 4.00), an indicator variable for whether or not the individual had obtained a graduate degree before wave I, and indicator variables for selectivity of their undergraduate program. In particular, using Barron's *Profiles of American Colleges*, we categorized universities as "least selective" (the omitted category), "moderately selective," or "more selective" in admissions.⁸

Professional background

We include years of total work experience, whether the individual had no job at the time of wave I, whether they were in school full-time, whether they were self-employed on their current job for 35 hours or more at the time of wave I, and two indicator variables representing whether they reported themselves as currently being a lower-level manager or a mid- to high-level manager.

Later life events

Because earnings are analyzed in a panel specification, we incorporate additional variables that reflect changes in participants' lives between wave I and the corresponding subsequent wave for each observation. Aside from age at the time of each wave, we in-

clude a dummy variable for whether or not the individual completed a graduate degree, and indicator variables for marriage (or cohabitation) status and children under 18 living in the home at the time of each wave.

Descriptive Statistics

Descriptive statistics of each of our wave I covariates are shown in Table 1 separately for women and men and by whether they were ever self-employed during waves II, III, or IV, or never self-employed (thus, traditionally employed). In the first two columns, means (with standard deviations in parentheses) for women are reported by self-employment and traditional employment and for men in the third and fourth columns, respectively. The last four columns report the difference in means across the different groups, with stars indicating significant differences at different levels.

Among women, 6.25% are ever self-employed, while this percentage is 10.3 for men. On average, self-employed individuals are nearly 29 years old. Both self-employed men and self-employed women are older than their counterparts in traditional employment, but there are no significant differences in age between self-employed men and self-employed women.

In terms of cognitive skills, men have significantly higher GMAT scores on average, especially on the quantitative portion of the exam. For the verbal portion, scores for men are significantly higher only in traditional employment. Regarding balance of cognitive skills, all groups are similar except for self-employed women, who as a group are more balanced (see Figure 1). In terms of non-cognitive skills, self-employed women have significantly higher levels than women in traditional employment, but there are no significant differences with respect to self-employed men. Kernel densities for the non-cognitive trait index are shown in Figure 2. Non-cognitive skill balance is similar across all groups, as shown in Figure 3.

Individual non-cognitive traits composing the non-cognitive trait index are also included in Table A1. In comparison with men in the same employment type, all women report higher communication skills, ability to organize, ability to motivate others and ethical standards, and lower shrewdness. Additionally, for traditional employment only, women report higher ability to work with people with diverse backgrounds, being a team player, having more initiative and more integrity, and being more physically attractive in comparison to men, although men report higher ability to adapt theory to practice. When comparing individual level non-cognitive traits for women across employment types, self-employed women report higher levels of integrity, initiative and assertiveness.

Some non-cognitive traits appear similar across self-employed men and women. Compared to their counterparts in traditional employment, both groups report greater ability to capitalize on change, to delegate tasks, and to understand business in other cultures compared to their counterparts in traditional employment. Interestingly, self-employed women are significantly more assertive than self-employed men (although assertiveness is traditionally considered a masculine trait).

Preferences regarding work-life balance and job characteristics also show distinct patterns. Interestingly, both men and women report equally high importance on family. However, both women in traditional employment and self-employment place higher importance on their careers than do men, while men place higher importance on wealth (though only in traditional employment). This is suggestive of the fact that the women in our sample are not necessarily representative of the general population of women who go into self-employment.

In comparison with men, women also place higher priority on all non-monetary aspects of their expected future job, such as having “good” hours, having enough authority to do their jobs, and having job security. Additionally, women in traditional employment also place more importance on their work being interesting and receiving good compensation when compared to men in traditional employment. Men in self-employment are similar to those in traditional employment, except that the latter place higher importance on job security and less importance on doing interesting work.

Additionally, demographic characteristics are included in Table A1. In our sample, a very low proportion of men are black, with higher proportions for women. While twice as many black men in our sample are in traditional employment compared to self-employment, there are no significant differences in participation of black women between both occupations. Within each employment group, men are more likely to be married than women. Similarly, men in traditional employment are more likely to have children.

Empirical Methodology

In this section, we examine the effect of non-cognitive traits, skill balance, and preferences on self-employment outcomes and performance. First, we explore the relationship between our variables of interest and the probability of being ever self-employed, and then we analyze how these variables affect self-employment earnings. For each exercise, we conduct estimations separately for men and for women.

Determinants of eventual self-employment

In this section, our variable of interest is the probability that, at some point in time during waves II, III and IV of the survey, individual i was observed in self-employment (ever self-employed).

Our regression equation for this part is:

$$\Pr(SE_i = 1) = \Phi(\alpha + G_i\beta + N_i\delta + CV_i\lambda + P_i\mu + X_i\theta + \epsilon_i) \quad (1)$$

where SE_i is an indicator for whether individual i was ever self-employed (self-employed in either wave II, wave III or wave IV of the survey), and Φ denotes the normal distribution. The first independent variables of interest are included in G_i , a two-dimensional vector containing our cognitive measures, the scores for for the verbal and quantitative components of the GMAT for individual i . N_i is the non-cognitive trait index constructed using principal component analysis.⁹ CV_i is the coefficient of variation in skills for an individual i which is a two-dimensional vector containing balance in GMAT scores and balance in non-cognitive traits. P_i contains preferences over work-life balance and job-related characteristics. X_i contains the vector of control variables detailed in the section above. The coefficients of interest are β , δ , λ , and μ whose dimensions are conformable with G_i , N_i , CV_i , and P_i .

Earnings

For the next section, we study the returns to self-employment compared to paid employment, as well as the returns to cognitive skills, skill balance, non-cognitive traits and preferences over lifestyle and job-related characteristics for each type of occupation. The purpose of this exercise is to explore whether or not the traits that are rewarded in self-employment are consistent with those that drive individuals into self-employment.

Our regression equation for the earnings analysis is:

$$\begin{aligned} \ln y_{iw} = & \zeta + G_i(\kappa_0 + \kappa_1 S_{iw}) + N_i(\phi_0 + \phi_1 S_{iw}) + CV_i(\mu_0 + \mu_1 S_{iw}) \\ & + P_i(\nu_0 + \nu_1 S_{iw}) + X_{iw}\rho + \psi S_{iw} + \tau_w + \xi_{iw} \end{aligned} \quad (2)$$

where y_{iw} is salary of individual i in wave w . S_{iw} is a dummy variable equal to one if individual i reported self employment as their primary job for 35 hours or more in wave w , for $w \in \{II, III, IV\}$. G_i , N_i , CV_i , and P_i are as defined for the ever-self-employed regression. Similarly, the coefficients of interest are $\kappa_k, \eta_k, \phi_k, \mu_k, \nu_k$ for $k = 0, 1$

corresponding to traditional employment and self-employment, respectively.

In the controls X_{iw} , we include some of the same wave-invariant controls included in the ever-self-employed regression, such as work experience at the time of wave I and demographic characteristics.¹⁰ Because we are focusing on earnings in a panel context, we additionally control for age of individual i at the time of each wave w . We also include binary variables that capture whether or not individual i had a graduate degree, whether or not individual i was married (or cohabiting with a partner), and whether or not individual i had kids younger than 18 living in the household, at the time of each wave w . Indicator variables for waves are also included.

Results

In this section, we present the result of the empirical exercises described in the previous section. First, we present the determinants of eventual self-employment, followed by the correlates of earnings.

Determinants of eventual self-employment

Our main results are presented in Table 2, which shows the marginal effect estimates for the predictors of eventual self-employment for men and for women separately. This table reveals stark differences between both groups.

For women, the probability of ever becoming self-employed is affected mainly by skills and skill balance. One additional point in the quantitative portion of the GMAT decreases the probability of becoming self-employed, though this effect is only significant at the 10% level. The relationship between non-cognitive traits and the probability of self-employment is stronger in terms of significance level, and has the opposite effect. Similarly, skill balance in cognitive skills is associated with a higher probability of self-employment, supporting Lazear's Jack-of-all-trades theory regarding selection into self-employment. None of the preference variables seem to matter for women, in terms of magnitudes or statistical significance – not even importance of family, in contrast with most of the literature about women in self-employment in the more general population (Gurley-Calvez et al., 2009; Leoni and Falk, 2010; Özcan, 2011).

In contrast, skills and skill balance are not significant drivers of self-employment for men, who are driven entirely by preferences about lifestyle and job-related characteristics. Men who prioritize their career are less likely to become self-employed, as well as men

who value job security and having “good” work hours, while those who value having interesting work are more likely to become self-employed. This result is in line with Benz and Frey (2008) and Hyytinen et al. (2013), and supports the existence of non-pecuniary benefits bearing weight in self-employment decisions, though only for men. We do not find any significant results with respect to “being one’s own boss” as in Hurst and Pugsley (2011), since having enough authority to do one’s job is not significant for either men or women.

Table A2 contains the same analysis with non-cognitive traits included at an individual level, with very similar results: women are mostly driven by several non-cognitive traits and by cognitive skill balance, while men are mainly driven by preferences. Self-employment is positively associated with more assertiveness, with a higher ability to understand business in other cultures, and negatively associated with having the ability to adapt theory to practice and with being a team player. At the 10% level, self-employed women have lower GMAT quantitative scores and higher ethical standards, as opposed to the “smart and illicit” result for men in Levine and Rubinstein (2017). For men, the only non-cognitive trait associated with a lower probability of becoming self-employed is the ability to work with individuals from diverse backgrounds, though it is only significant at the 10% level.¹¹

Earnings

In terms of earnings, the results of our analysis, presented in Table 3, reveal similar factors being rewarded across groups for both employment types. Both men and women experience higher earnings when equipped with higher quantitative skills. Additionally, those who prioritize interesting and challenging work, alongside those valuing monetary compensation, tend to enjoy higher salaries. Conversely, individuals emphasizing job security face an earnings penalty. Table A7 in the appendix presents similar results including individual non-cognitive traits. Assertiveness and initiative are positively associated with higher earnings, while ethics appears to incur a penalty for both men and women. Notably, few traits are uniquely associated with earnings within each group: for both types of employment, only women experience a beauty premium and are rewarded for being a team player, while only men benefit from connections.

Surprisingly, none of the traits associated with higher earnings among the self-employed align with those influencing the likelihood of pursuing self-employment. For women, there is an additional earnings premium for women with higher quantitative skills who are self-employed. Although they are an important driver of self-employment for women,

non-cognitive traits at the aggregate level and balance in cognitive skills are not significantly related to higher earnings. In contrast, though preferences do not influence women opting into self-employment, assigning importance to wealth is positively associated with higher earnings in this activity. Of the non-cognitive traits, only the ability to adapt theory to practice is significantly associated with higher self-employment earnings at the 5% level.

None of the traits or preferences that are associated with higher earnings for self-employed women are significant for self-employed men. For men, balance in non-cognitive traits is associated with higher self-earnings, although it is not a determinant of self-employment. In terms of individual non-cognitive traits, there is an earnings penalty for those who are able to capitalize on change, and a beauty premium.¹²

Given the above results for men, our analysis partially supports Lazear's Jack-of-all-trades theory in terms of performance in self-employment. We observe that self-employed men with a balanced set of non-cognitive skills tend to earn more, though this correlation between skill balance and earnings does not appear to be present for women. While the point estimate for non-cognitive skill balance is positive for women, it is not statistically significant. However, as Figure 1 shows, self-employed women as a group are more balanced in terms of cognitive skills compared to all other groups, and thus there is less variation to leverage for women as for men.

Discussion and Conclusion

This study explores differences in the factors influencing self-employment entry and earnings among men and women who are career-oriented business professionals. For women, higher levels of non-cognitive traits and a more balanced mix of cognitive skills increase the probability of self-employment, while preferences regarding work-life balance and job attributes do not seem to matter. In contrast, self-employed men are driven by their preferences over work-life balance, such as de-prioritizing their career, and preferences over job related characteristics such as valuing interesting work or job security.

Regarding earnings, both men and women benefit from quantitative skills and from valuing both challenging work and compensation, while prioritizing job security is penalized in both traditional employment and self-employment. Among the self-employed, however, the characteristics associated with higher earnings differ between the two groups. Self-employed women with high quantitative skills and those who value wealth earn more. For self-employed men, there is a premium for those who have more balanced

non-cognitive skills, and a penalty for those who value authority. This finding for women could help to explain the relative under-performance of women in business and finance from Bertrand et al. (2010), in that women with higher quantitative skills select out of self-employment despite these skills being highly rewarded in that sector.

Our findings offer partial support for Lazear's Jack-of-all-trades theory, with men and women each aligning with a different aspect of its predictions. For women, having a more balanced skill set—a "Jacqueline-of-all-trades" profile—is associated with selection into self-employment, but not with higher earnings. For men, the reverse holds: a balanced skill set—a Jack-of-all-trades profile—is linked to greater earnings, but not to self-employment entry. Interestingly, the traits that drive men and women into self-employment are not the ones that get rewarded in self-employment, suggesting that non-pecuniary benefits are important considerations in studying self-employment decisions and outcomes.

More broadly, given our selected sample, our results also contribute to the literature that studies the characteristics of women in competitive environments. In some competitive environments, such as professional tennis (Jetter and Walker, 2015; Paserman, 2010; Wozniak, 2012; Cohen-Zada et al., 2017), and professional track and field athletics (Frick, 2011), women compete against other women only. Other competitive environments where women compete against men are largely comprised of men, such as professional chess (Gerdes and Gränsmark, 2010; Gränsmark, 2012). In both types of studies, results are mixed. Some studies show that the women resemble the men in these fields (Jetter and Walker, 2015), while others find both behavioral and performance differences between men and women. These differences may be consistent with traditional explanations, such as women being less competitive or more risk averse (Paserman, 2010; Frick, 2011; Gerdes and Gränsmark, 2010), or counter-intuitive, such as women responding better to competitive pressure (Cohen-Zada et al., 2017). Other studies focus on one-time competitions that both men and women voluntarily sign up for, where women compete against men (Nekby et al., 2008; Lindquist and Säve-Söderbergh, 2011; Garratt et al., 2013; Jetter and Walker, 2018). These studies show that women's traits are similar to those of the men in these environments, and more extreme than those of the men in some cases.

Our results add to this body of literature by shedding light into motivations, preferences and skills that lead women to enter a competitive occupation where men and women "compete" against each other for both resources and survival. We show that, among business professionals, self-employed women differ from self-employed men in terms of both the factors driving them and their performance. However, in the sports examples, although they are legitimate workplaces for athletes, the rules for succeeding are

clear-cut, each match or race has a definite starting and ending point, and the outcome of each match or race is either a win or a loss. These characteristics provide constant feedback and allow athletes to constantly assess their performance and adjust their training strategies.

In contrast, owning a company is a 24/7 job, where rules are not clear cut, are many times learned on-the-go, and the outcome is more difficult to observe, especially during the start-up period. Using the terminology about learning environments in Hogarth et al. (2015), while sports can be considered a “kind” environment, self-employment resembles a “wicked” environment.¹³ In contrast to a kind learning environment, a wicked learning environment may lead to reinforcement of incorrect strategies and behaviors, opening up the possibility for psychological or behavioral differences between the men and women who succeed in each of these environments to arise and possibly persist. This is in line with what we find in terms of what drives individuals and what makes them successful.

Regarding preferences, our results are in stark contrast to studies suggesting that non-pecuniary reasons are important motivators for women (Tegtmeier et al., 2016). Perhaps because our sample focuses on individuals who have demonstrated commitment to their careers and are employed full-time, our findings suggest that it is men, and not women, who are potentially driven into self-employment for non-pecuniary reasons. Combining this result with Hogarth et al. (2015)’s theory, the fact that learning is more noisy in a wicked environment might perpetuate the discrepancy between the drivers of self-employment and the traits that make them successful. In any case, policies attempting to encourage women’s participation in businesses should account for potential differences in both the motivators for entering self-employment and the traits that are ultimately rewarded.

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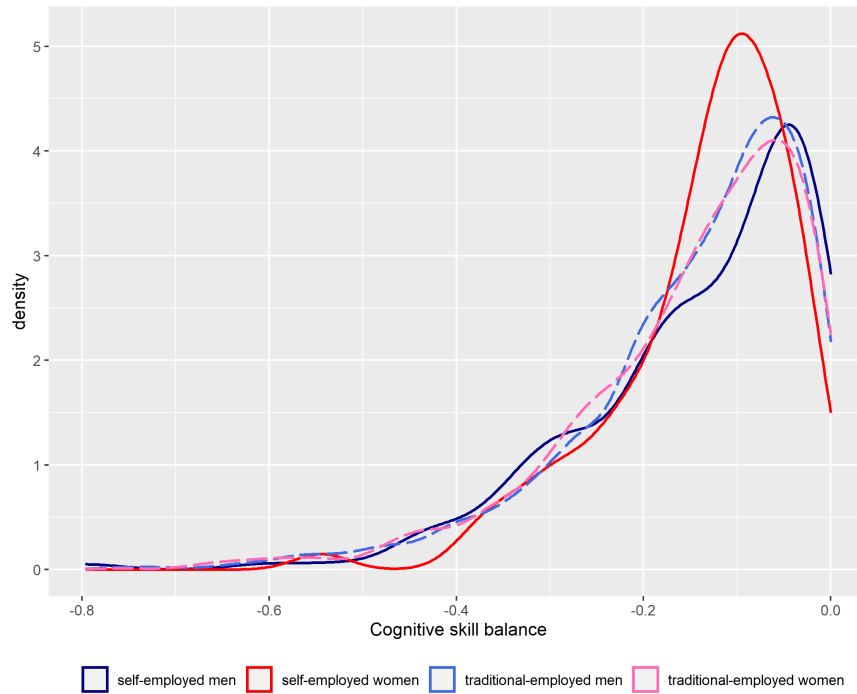


FIGURE 1: Kernel Densities of Cognitive Skill Balance

Notes: The figure above plots kernel densities separately for self-employed men (solid blue), self-employed women (solid red), traditionally employed men (dashed light blue) and traditionally employed women (dashed pink). The construction of skill balance is detailed in the Data section. The variable takes a max value of zero for the most balanced and declines as the cognitive skills are less balanced. As the figure shows, self-employed women are more balanced in terms of cognitive skills as a group.

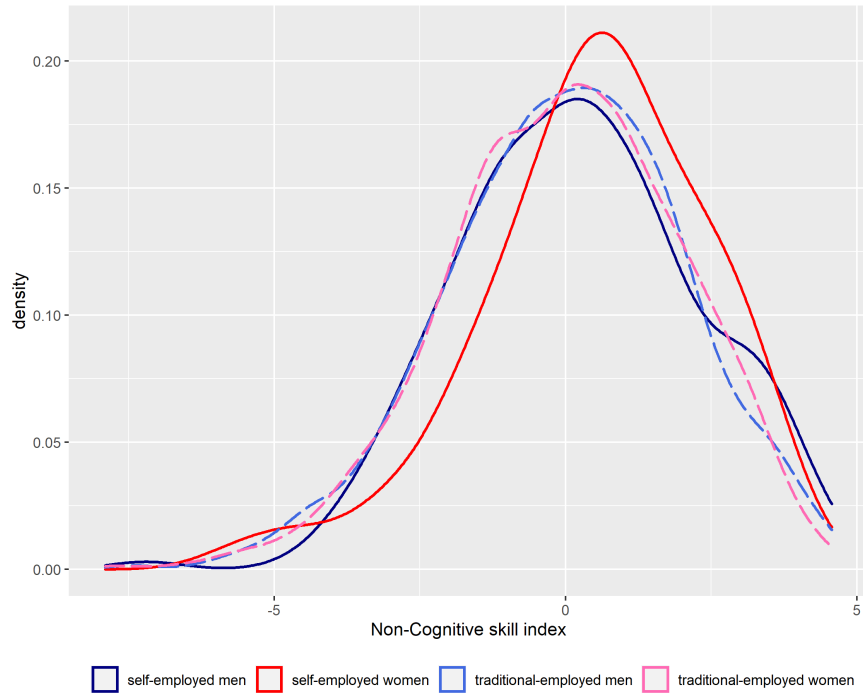


FIGURE 2: Kernel Densities of Non-Cognitive Skill Index

Notes: The figure above plots kernel densities separately for self-employed men (solid blue), self-employed women (solid red), traditionally employed men (dashed blue) and traditionally employed women (dashed red). The construction of the non-cognitive skill index using principal component analysis (PCA) and is detailed in the Data section. The variable is mean zero and standard deviation of one separately for men and women. As it can be seen, self employed women have higher self-perceived non-cognitive skills compared to the other groups.

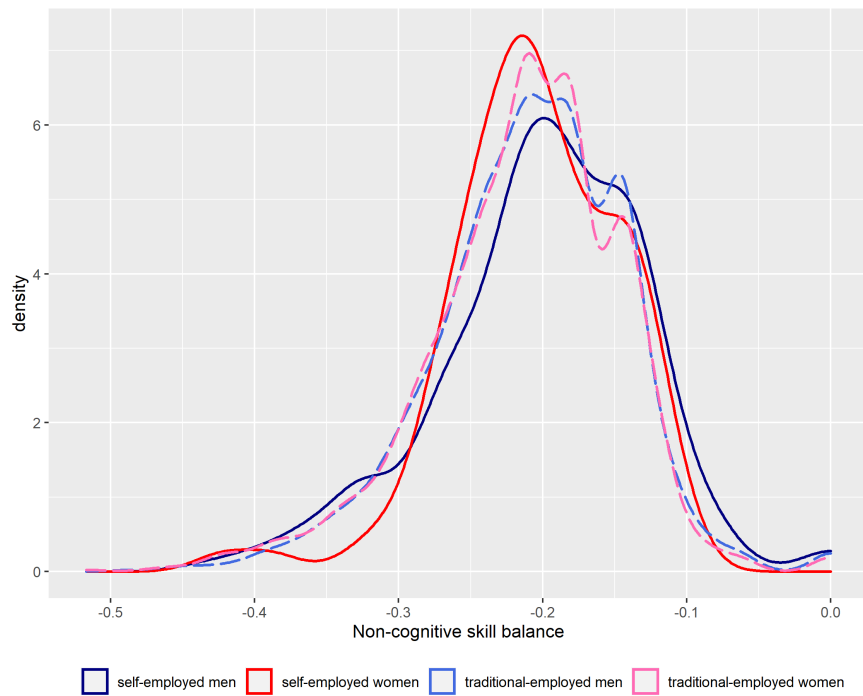


FIGURE 3: Kernel Densities of Non-Cognitive Skill Balance

Notes: The figure above plots kernel densities separately for self-employed men (solid blue), self-employed women (solid red), traditionally employed men (dashed blue) and traditionally employed women (dashed red). The construction of skill balance is detailed in the Data section. The variable takes a max value of zero for the most balanced and declines as the non-cognitive skills are less balanced. The figure shows that all groups are relatively similar.

TABLE 1: Descriptive statistics and t-tests for differences in means

Variable	Women		Men		Employment differences (Trad - Self)		Group differences (Men - Women)	
	Self emp	Trad emp	Self emp	Trad emp	Women	Men	Self emp	Trad emp
<u>Cognitives</u>								
Quantitative GMAT	25.77 (7.67)	26.65 (8.01)	30.87 (7.70)	31.07 (8.58)	0.88	0.20	5.10***	4.42***
Verbal GMAT	28.00 (8.76)	27.70 (7.74)	28.72 (7.87)	29.13 (7.78)	-0.30	0.41	0.72	1.43***
<u>Non-cognitives</u>								
Index	0.47 (1.96)	-0.03 (2.00)	0.20 (2.03)	-0.02 (2.03)	-0.50**	-0.22	-0.27	0.01
<u>Skill Balance</u>								
Non-cognitives	-0.21 (0.06)	-0.21 (0.07)	-0.20 (0.07)	-0.21 (0.07)	-0.01	-0.01*	0.01	0.00
Cognitives	-0.14 (0.10)	-0.15 (0.13)	-0.14 (0.13)	-0.15 (0.12)	-0.01	-0.01	-0.00	0.00
<u>Work-Life Balance</u>								
Family	0.89 (0.31)	0.88 (0.32)	0.89 (0.31)	0.88 (0.33)	-0.01	-0.02	0.00	-0.01
Career	0.71 (0.45)	0.69 (0.46)	0.57 (0.50)	0.61 (0.49)	-0.03	0.05	-0.15**	-0.07***
Wealth	0.18 (0.38)	0.18 (0.38)	0.24 (0.43)	0.25 (0.44)	0.00	0.02	0.06	0.08***
<u>Job Preferences</u>								
Interesting Work	0.87 (0.34)	0.90 (0.30)	0.89 (0.32)	0.85 (0.36)	0.04	-0.04*	0.02	-0.06***
Authority	0.81 (0.39)	0.78 (0.42)	0.69 (0.46)	0.72 (0.45)	-0.04	0.03	-0.12**	-0.06***
Job security	0.53 (0.50)	0.58 (0.49)	0.38 (0.49)	0.48 (0.50)	0.05	0.09***	-0.14**	-0.10***
Compensation	0.63 (0.49)	0.68 (0.47)	0.60 (0.49)	0.63 (0.48)	0.05	0.04	-0.03	-0.04**
Challenging Work	0.33 (0.47)	0.31 (0.46)	0.27 (0.45)	0.29 (0.45)	-0.02	0.01	-0.06	-0.02
No conflicting demands	0.23 (0.42)	0.21 (0.41)	0.19 (0.39)	0.18 (0.38)	-0.02	-0.01	-0.04	-0.04***
Hours	0.32 (0.47)	0.37 (0.48)	0.18 (0.39)	0.24 (0.43)	0.05	0.05*	-0.14**	-0.13***
Observations	91	1365	213	1859				

Notes: The first column in the table above lists our main variables of interest by variable category in each row. In the second through fifth columns, we list the means and standard deviations (below in parenthesis) for each variable for men and women and by whether a respondent is ever self-employed in waves II, III, or IV of the GMAT Registrant Survey. In the sixth through ninth columns, we present a difference in means by comparing employment differences (traditionally employed minus self-employed) across women, then men, and then comparing group differences (men minus women) for self-employed, then traditionally employed. We report differences in means that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$. More details on variable definitions can be found in the Data Section.

TABLE 2: Predictors of Eventual Self-employment

		Women	Men
Cognitives:	Quantitative GMAT	-0.002*	0.000
		(0.001)	(0.001)
	Verbal GMAT	0.002	-0.002
		(0.001)	(0.001)
Non-cognitives:	Index	0.012**	0.005
		(0.005)	(0.005)
Skill Balance:	Non-cognitives	-0.130	0.088
		(0.135)	(0.140)
	Cognitives	0.107**	0.083
		(0.051)	(0.060)
Work-Life Balance:	Family	0.007	0.012
		(0.019)	(0.020)
	Career	-0.002	-0.029**
		(0.014)	(0.014)
	Wealth	-0.001	0.004
		(0.016)	(0.016)
Job Characteristics:	Interesting Work	-0.029	0.039**
		(0.019)	(0.020)
	Authority	0.006	-0.022
		(0.017)	(0.016)
	Job security	-0.002	-0.028*
		(0.013)	(0.015)
	Compensation	-0.022	-0.002
	(0.013)	(0.015)	
	Challenging Work	-0.003	0.001
		(0.014)	(0.015)
	No conflicting demands	0.010	0.029
		(0.015)	(0.018)
	Hours	-0.011	-0.030*
		(0.015)	(0.018)
Observations		1,456	2,072

Notes: The table above reports estimates and standard errors (in parenthesis below) for regressions of the listed variables on a binary indicator for a respondent ever being self employed as detailed in the Data section. The first column reports estimates for women and the second column for men where each is estimated separately. We do not report coefficients for control variables despite their inclusion. These variables include race/ethnicity, age, marriage status, presence of children under 18, family background, academic variables, and professional background as detailed in the Data section. We report estimates that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$ using robust standard errors. The specification is detailed in its entirety in the Empirical Methodology Section.

TABLE 3: Earnings Regressions

		Women		Men	
		× Self-emp		× Self-emp	
	Self-emp	-0.502 (0.562)		0.140 (0.381)	
Cognitives:	Quantitative GMAT	0.010*** (0.002)	0.025* (0.013)	0.009*** (0.001)	0.003 (0.008)
	Verbal GMAT	-0.001 (0.002)	-0.023 (0.015)	0.000 (0.002)	0.010 (0.009)
Non-cognitives:	Index	0.011 (0.007)	0.016 (0.051)	0.007 (0.006)	-0.036 (0.032)
Skill Balance:	Non-cognitives	0.055 (0.206)	0.347 (1.781)	0.218 (0.178)	1.667* (0.874)
	Cognitives	0.054 (0.086)	-0.669 (0.740)	0.072 (0.079)	-0.187 (0.401)
Work-Life Balance:	Family	0.036 (0.029)	0.039 (0.225)	0.021 (0.028)	-0.194* (0.114)
	Career	0.002 (0.022)	-0.212 (0.174)	0.013 (0.018)	0.129 (0.099)
	Wealth	-0.018 (0.028)	0.436* (0.237)	0.041* (0.022)	-0.147 (0.121)
Job Characteristics:	Interesting Work	0.081** (0.034)	0.425 (0.370)	0.043* (0.023)	0.068 (0.168)
	Authority	-0.033 (0.026)	0.167 (0.308)	0.022 (0.021)	-0.341*** (0.122)
	Job security	-0.059** (0.024)	-0.296 (0.226)	-0.086*** (0.019)	0.032 (0.122)
	Compensation	0.085*** (0.024)	0.225 (0.265)	0.075*** (0.020)	0.187 (0.118)
	Challenging Work	0.076*** (0.023)	0.029 (0.196)	0.052*** (0.020)	0.135 (0.116)
	No conflicting demands	-0.004 (0.027)	0.050 (0.256)	-0.039 (0.024)	0.145 (0.122)
	Hours	-0.045** (0.023)	-0.174 (0.253)	-0.029 (0.022)	-0.151 (0.147)
Observations		2,937		4,239	
R ²		0.345		0.379	

Notes: The table above reports coefficient estimates and standard errors (in parenthesis below) for regressions of the listed variables on the log of annual earnings as detailed in the Data section. The first two columns report estimates for women with the second of the two columns reporting the estimate for the stated variable interacted with a binary indicated for ever self-employed in waves II, III, or IV. The third and fourth columns repeat this for men. We do not report coefficients for control variables despite their inclusion. These variables include race/ethnicity, age, marriage status, presence of children under 18, family background, academic variables, and professional background as detailed in the Data Section. We report estimates that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$ using robust standard errors. The specification is detailed in its entirety in the Empirical Methodology Section.

Notes

¹The GMAT requirement for admission into MBA programs has changed since the Covid-19 pandemic, with many programs offering waivers.

²The GMAT Registrant Survey asks respondents only about jobs where the respondent works 35 or more hours and does not identify self-employment performed for less than 35 hours per week in Wave 2. Because of this restriction, and to focus on serious commitments to self-employment, we consider full-time jobs to entail at least 35 hours in a typical work week.

³The startup failure rate is 90%, see Schroeder (2023).

⁴Earnings could be reported in the survey in a variety of ways: hourly, weekly, twice a month, monthly, or yearly. For those not reporting an hourly wage, we used reported hours worked per week to calculate a measure of hourly wage, assuming 52 weeks worked per year.

⁵Some argue that self-reports may be subject to reference bias (West et al., 2016).

⁶Cobb-Clark and Schurer (2012, 2013); Elkins et al. (2017) find evidence that personality traits are relatively stable for individuals of working age, and that life events do not tend to affect personality traits (Elkins et al., 2017). An exception that may be relevant to our case is marriage, which reduces openness to experience, but the results we obtain do not relate to this trait.

⁷See (Blanchflower and Oswald, 1998; Dunn and Holtz-Eakin, 2000; Fairlie, 1999; Hundley, 2006)

⁸The more numerous admissions selectivity categories included in Barron's guide were collapsed into these three categories, where the omitted category ("least selective") was also combined with those schools not included in the guide.

⁹In Table A2 we report estimates where we replace the index with a 16-dimensional vector containing each of the 16 self-assessed non-cognitive traits separately (including nine soft skills, five personality characteristics and two other factors deemed important for success in business).

¹⁰Due to the possibility of missing information on jobs held between waves, we are only able to control for total work experience as of wave I, though age is included and is time-variant.

¹¹Table A3 and Table A4 show probit estimates for ever self-employed, including the non-cognitive skill index and individual non-cognitive skills, respectively; Table A5 and Table A6 show similar results using a linear probability model.

¹²In consideration of the possibility these differences may be influenced by earnings differentials across industries, we examined some limited information on industries available in the surveys. In each wave, respondents reported their industry as one of ten sectors: agriculture; mining; construction; manufacturing; transportation; wholesale; retail; finance; services; or public administration. Between Waves 2–4, the industry distribution is similar for self-employed and traditionally employed respondents: manufacturing and construction have larger shares of men, and services have a larger share of women for both traditionally employed and self-employed. The only sector with a statistically significant differential in employment that is unique among self-employed is transportation, which has a larger share of women. These patterns suggest relatively little sorting into industries by self-employment status.

¹³According to Hogarth et al. (2015), in a wicked learning environment, feedback on one's actions is noisy, making it harder for an individual to effectively learn from their experiences.

1 Online Appendix

TABLE A1: Additional Descriptive statistics and t-tests for differences in means for individual non-cognitive traits and demographics

Variable	Women		Men		Employment differences (Trad - Self)		Group differences (Male - Female)	
	Self emp	Trad emp	Self emp	Trad emp	Women	Men	Self emp	Trad emp
<u>Non-cognitives</u>								
Communication	3.49 (0.58)	3.42 (0.59)	3.36 (0.63)	3.33 (0.62)	-0.07	-0.03	-0.14*	-0.10***
Work with diverse back- grounds	3.65 (0.50)	3.65 (0.55)	3.55 (0.55)	3.59 (0.58)	0.01	0.04	-0.10	-0.07***
Ability to organize	3.59 (0.60)	3.61 (0.56)	3.41 (0.63)	3.43 (0.63)	0.02	0.02	-0.18**	-0.18***
Capitalize on Change	3.31 (0.64)	3.16 (0.65)	3.28 (0.61)	3.19 (0.66)	-0.15**	-0.09**	-0.03	0.03
Delegate tasks	3.41 (0.63)	3.23 (0.70)	3.34 (0.62)	3.25 (0.69)	-0.18**	-0.09**	-0.07	0.02
Adapt theory to practice	3.13 (0.79)	3.13 (0.67)	3.27 (0.61)	3.20 (0.68)	-0.00	-0.07	0.14	0.07***
Understand other cul- tures	2.81 (0.87)	2.55 (0.86)	2.77 (0.88)	2.60 (0.89)	-0.26***	-0.17***	-0.05	0.05
Motivate others	3.45 (0.65)	3.32 (0.62)	3.28 (0.65)	3.27 (0.65)	-0.13*	-0.01	-0.17**	-0.04**
Team player	3.56 (0.64)	3.65 (0.57)	3.52 (0.60)	3.58 (0.61)	0.09	0.06	-0.04	-0.07***
Integrity	3.47 (0.62)	3.35 (0.63)	3.38 (0.64)	3.31 (0.64)	-0.12*	-0.07	-0.09	-0.05**
Initiative	3.71 (0.50)	3.61 (0.52)	3.63 (0.51)	3.56 (0.53)	-0.11*	-0.07*	-0.09	-0.04**
Assertiveness	3.43 (0.56)	3.20 (0.64)	3.18 (0.65)	3.16 (0.66)	-0.23***	-0.02	-0.25***	-0.04
Ethical standards	3.82 (0.41)	3.76 (0.46)	3.66 (0.59)	3.64 (0.54)	-0.06	-0.03	-0.16***	-0.12***
Shrewdness	2.60 (0.66)	2.62 (0.76)	2.82 (0.79)	2.78 (0.74)	0.02	-0.05	0.22**	0.15***
Physically attractive	3.09 (0.59)	3.13 (0.57)	3.02 (0.61)	3.03 (0.59)	0.04	0.00	-0.06	-0.10***
Connections	2.57 (0.78)	2.54 (0.76)	2.59 (0.88)	2.58 (0.77)	-0.03	-0.02	0.02	0.04
<u>Demographics</u>								
Asian	0.18 (0.38)	0.15 (0.35)	0.17 (0.38)	0.15 (0.36)	-0.03	-0.02	-0.00	0.00
Black	0.14 (0.35)	0.17 (0.37)	0.05 (0.21)	0.08 (0.28)	0.02	0.04**	-0.10**	-0.08***
Hispanic	0.14 (0.35)	0.16 (0.37)	0.19 (0.40)	0.16 (0.37)	0.02	-0.03	0.05	0.00
Married	0.31 (0.46)	0.30 (0.46)	0.41 (0.49)	0.38 (0.49)	-0.01	-0.03	0.11*	0.08***
Has children	0.20 (0.40)	0.12 (0.33)	0.24 (0.43)	0.19 (0.39)	-0.07*	-0.05*	0.04	0.06***
Age	28.84 (6.95)	26.62 (5.42)	28.85 (7.00)	27.66 (5.78)	-2.22***	-1.19**	0.01	1.04***
Observations	91	1365	213	1859				

Notes: The first column in the table above lists our main variables of interest by variable category in each row. In the second through fifth columns, we list the means and standard deviations (below in parenthesis) for each variable for men and women and by whether a respondent is ever self-employed in waves II, III, or IV of the GMAT Registrant Survey. In the sixth through ninth columns, we present a difference in means by comparing employment differences (traditionally employed minus self-employed) across women, then men, and then comparing group differences (men minus women) for self-employed, then traditionally employed. We report differences in means that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$. More details on variable definitions can be found in the Data Section.

TABLE A2: Predictors of Eventual Self-employment with Individual Traits (Probit Marginal Effects)

		Women	Men
Cognitives:	Quantitative GMAT	-0.002* (0.001)	0.000 (0.001)
	Verbal GMAT	0.002 (0.001)	-0.002* (0.001)
Non-cognitives:	Communication	0.001 (0.011)	0.006 (0.012)
	Work with diverse backgrounds	-0.011 (0.011)	-0.022* (0.012)
	Ability to organize	-0.001 (0.011)	-0.010 (0.011)
	Capitalize on Change	0.005 (0.011)	0.013 (0.012)
	Delegate tasks	0.019* (0.011)	0.017 (0.011)
	Adapt theory to practice	-0.025** (0.011)	0.001 (0.011)
	Understand other cultures	0.016** (0.008)	0.011 (0.009)
	Motivate others	0.023* (0.012)	-0.012 (0.011)
	Team player	-0.024** (0.011)	-0.003 (0.011)
	Integrity	0.003 (0.011)	0.007 (0.012)
	Initiative	0.008 (0.014)	0.022 (0.014)
	Assertiveness	0.033*** (0.011)	-0.002 (0.012)
	Ethical standards	0.027* (0.015)	0.002 (0.013)
	Shrewdness	-0.009 (0.010)	0.006 (0.010)
	Physically attractive	-0.003 (0.011)	0.005 (0.012)
	Connections	-0.007 (0.011)	-0.011 (0.011)
	Skill Balance:	Non-cognitives	-0.015 (0.168)
Cognitives		0.113** (0.051)	0.087 (0.060)
Work-Life Balance:	Family	0.007 (0.020)	0.016 (0.021)
	Career	-0.001 (0.014)	-0.032** (0.014)
	Wealth	-0.001 (0.016)	0.001 (0.017)
Job Characteristics:	Interesting Work	-0.028 (0.019)	0.040** (0.020)
	Authority	0.002 (0.016)	-0.023 (0.016)
	Job security	0.000 (0.013)	-0.025* (0.015)
	Compensation	-0.021 (0.013)	-0.005 (0.014)
	Challenging Work	-0.005 (0.014)	-0.002 (0.015)
	No conflicting demands	0.006 (0.015)	0.027 (0.018)
	Hours	-0.007 (0.014)	-0.028 (0.018)
Observations	1,456	2,072	

Notes: The table above reports estimates and standard errors (in parenthesis below) for regressions of the listed variables on a binary indicator for a respondent ever being self employed as detailed in the Data section. The first column reports estimates for women and the second column for men where each is estimated separately. We do not report coefficients for control variables despite their inclusion. These variables include race/ethnicity, age, marriage status, presence of children under 18, family background, academic variables, and professional background as detailed in the Data section. We report estimates that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$ using robust standard errors. The specification is detailed in its entirety in the Empirical Methodology Section.

TABLE A3: Predictors of Eventual Self-employment (Probit Estimates)

		Women	Men
Cognitives:	Quantitative GMAT	-0.020*	0.000
		(0.011)	(0.007)
	Verbal GMAT	0.015	-0.013*
		(0.011)	(0.008)
Non-cognitives:	Index	0.101**	0.033
		(0.045)	(0.030)
Skill Balance:	Non-cognitives	-1.139	0.540
		(1.183)	(0.860)
	Cognitives	0.938**	0.510
		(0.448)	(0.371)
Work-Life Balance:	Family	0.061	0.075
		(0.170)	(0.125)
	Career	-0.021	-0.180**
		(0.121)	(0.085)
	Wealth	-0.011	0.024
		(0.142)	(0.099)
Job Characteristics:	Interesting Work	-0.258	0.241**
		(0.170)	(0.122)
	Authority	0.055	-0.135
		(0.146)	(0.099)
	Job security	-0.017	-0.172*
		(0.116)	(0.090)
	Compensation	-0.189	-0.015
	(0.117)	(0.091)	
	Challenging Work	-0.028	0.008
		(0.123)	(0.094)
	No conflicting demands	0.087	0.177
		(0.135)	(0.112)
	Hours	-0.093	-0.182*
		(0.129)	(0.109)
Observations		1,456	2,072

Notes: The table above reports estimates and standard errors (in parenthesis below) for regressions of the listed variables on a binary indicator for a respondent ever being self employed as detailed in the Data section. The first column reports estimates for women and the second column for men where each is estimated separately. We do not report coefficients for control variables despite their inclusion. These variables include race/ethnicity, age, marriage status, presence of children under 18, family background, academic variables, and professional background as detailed in the Data section. We report estimates that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$ using robust standard errors. The specification is detailed in its entirety in the Empirical Methodology Section.

TABLE A4: Predictors of Eventual Self-employment with Individual Traits (Probit Estimates)

		Women	Men
Cognitives:	Quantitative GMAT	-0.021* (0.011)	0.001 (0.007)
	Verbal GMAT	0.015 (0.011)	-0.014* (0.008)
Non-cognitives:	Communication	0.007 (0.102)	0.039 (0.074)
	Work with diverse backgrounds	-0.105 (0.105)	-0.134* (0.072)
	Ability to organize	-0.007 (0.101)	-0.063 (0.069)
	Capitalize on Change	0.044 (0.100)	0.078 (0.076)
	Delegate tasks	0.179* (0.096)	0.104 (0.070)
	Adapt theory to practice	-0.229** (0.103)	0.004 (0.068)
	Understand other cultures	0.151** (0.075)	0.068 (0.058)
	Motivate others	0.207* (0.113)	-0.073 (0.071)
	Team player	-0.218** (0.102)	-0.021 (0.066)
	Integrity	0.025 (0.104)	0.041 (0.072)
	Initiative	0.070 (0.132)	0.137 (0.088)
	Assertiveness	0.306*** (0.098)	-0.010 (0.076)
	Ethical standards	0.248* (0.139)	0.013 (0.080)
	Shrewdness	-0.079 (0.087)	0.039 (0.065)
	Physically attractive	-0.031 (0.102)	0.032 (0.077)
	Connections	-0.068 (0.099)	-0.067 (0.069)
	Skill Balance:	Non-cognitives	-0.136 (1.543)
Cognitives		1.040** (0.468)	0.541 (0.373)
Work-Life Balance:	Family	0.066 (0.181)	0.097 (0.129)
	Career	-0.011 (0.125)	-0.196** (0.086)
	Wealth	-0.013 (0.145)	0.009 (0.103)
Job Characteristics:	Interesting Work	-0.255 (0.176)	0.247** (0.122)
	Authority	0.018 (0.146)	-0.143 (0.099)
	Job security	0.003 (0.119)	-0.157* (0.091)
	Compensation	-0.191 (0.121)	-0.034 (0.090)
	Challenging Work	-0.049 (0.127)	-0.010 (0.093)
	No conflicting demands	0.055 (0.142)	0.168 (0.112)
	Hours	-0.063 (0.132)	-0.176 (0.110)
Observations	1,456	2,072	

Notes: The table above reports estimates and standard errors (in parenthesis below) for regressions of the listed variables on a binary indicator for a respondent ever being self employed as detailed in the Data section. The first column reports estimates for women and the second column for men where each is estimated separately. We do not report coefficients for control variables despite their inclusion. These variables include race/ethnicity, age, marriage status, presence of children under 18, family background, academic variables, and professional background as detailed in the Data section. We report estimates that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$ using robust standard errors. The specification is detailed in its entirety in the Empirical Methodology Section.

TABLE A5: Predictors of Eventual Self-employment (Linear Probability Model)

		Women	Men
Cognitives:	Quantitative GMAT	-0.002*	-0.000
		(0.001)	(0.001)
	Verbal GMAT	0.002	-0.002
		(0.001)	(0.001)
Non-cognitives:	Index	0.012**	0.005
		(0.005)	(0.005)
Skill Balance:	Non-cognitives	-0.130	0.092
		(0.125)	(0.147)
	Cognitives	0.101**	0.086
		(0.046)	(0.060)
Work-Life Balance:	Family	0.007	0.010
		(0.020)	(0.019)
	Career	-0.002	-0.028*
		(0.014)	(0.014)
	Wealth	0.002	0.004
		(0.017)	(0.016)
Job Characteristics:	Interesting Work	-0.034	0.036**
		(0.024)	(0.018)
	Authority	0.006	-0.020
		(0.016)	(0.017)
	Job security	-0.003	-0.027*
		(0.014)	(0.015)
	Compensation	-0.021	-0.001
	(0.014)	(0.015)	
	Challenging Work	-0.002	0.001
		(0.015)	(0.015)
	No conflicting demands	0.007	0.029
		(0.017)	(0.019)
	Hours	-0.013	-0.028*
		(0.015)	(0.016)
Observations		1,456	2,072
R ²		0.044	0.079

Notes: The table above reports estimates and standard errors (in parenthesis below) for regressions of the listed variables on a binary indicator for a respondent ever being self employed as detailed in the Data section. The first column reports estimates for women and the second column for men where each is estimated separately. We do not report coefficients for control variables despite their inclusion. These variables include race/ethnicity, age, marriage status, presence of children under 18, family background, academic variables, and professional background as detailed in the Data section. We report estimates that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$ using robust standard errors. The specification is detailed in its entirety in the Empirical Methodology Section.

TABLE A6: Predictors of Eventual Self-employment with Individual Traits (Linear Probability Model)

		Women	Men	
Cognitives:	Quantitative GMAT	-0.002 (0.001)	0.000 (0.001)	
	Verbal GMAT	0.002 (0.001)	-0.002 (0.001)	
Non-cognitives:	Communication	-0.000 (0.011)	0.007 (0.012)	
	Work with diverse backgrounds	-0.008 (0.012)	-0.021* (0.012)	
	Ability to organize	-0.004 (0.012)	-0.010 (0.011)	
	Capitalize on Change	0.007 (0.012)	0.012 (0.012)	
	Delegate tasks	0.018 (0.011)	0.016 (0.011)	
	Adapt theory to practice	-0.025* (0.013)	0.000 (0.011)	
	Understand other cultures	0.020** (0.010)	0.011 (0.010)	
	Motivate others	0.020 (0.013)	-0.012 (0.012)	
	Team player	-0.022 (0.013)	-0.004 (0.011)	
	Integrity	0.008 (0.012)	0.006 (0.011)	
	Initiative	0.010 (0.013)	0.021 (0.014)	
	Assertiveness	0.031*** (0.011)	-0.003 (0.013)	
	Ethical standards	0.022 (0.014)	0.002 (0.013)	
	Shrewdness	-0.004 (0.009)	0.006 (0.011)	
	Physically attractive	-0.000 (0.012)	0.007 (0.013)	
	Connections	-0.002 (0.012)	-0.009 (0.011)	
	Skill Balance:	Non-cognitives	-0.152 (0.176)	0.073 (0.186)
		Cognitives	0.102** (0.048)	0.091 (0.059)
Work-Life Balance:	Family	0.006 (0.020)	0.013 (0.020)	
	Career	-0.002 (0.014)	-0.029** (0.015)	
	Wealth	0.002 (0.017)	0.000 (0.017)	
Job Characteristics:	Interesting Work	-0.035 (0.024)	0.037** (0.018)	
	Authority	0.003 (0.016)	-0.022 (0.017)	
	Job security	-0.003 (0.014)	-0.025* (0.015)	
	Compensation	-0.019 (0.014)	-0.002 (0.015)	
	Challenging Work	-0.003 (0.016)	-0.000 (0.015)	
	No conflicting demands	0.003 (0.017)	0.028 (0.019)	
	Hours	-0.009 (0.015)	-0.028* (0.017)	
Observations	1,456	2,072		
R ²	0.062	0.085		

Notes: The table above reports estimates and standard errors (in parenthesis below) for regressions of the listed variables on a binary indicator for a respondent ever being self employed as detailed in the Data section. The first column reports estimates for women and the second column for men where each is estimated separately. We do not report coefficients for control variables despite their inclusion. These variables include race/ethnicity, age, marriage status, presence of children under 18, family background, academic variables, and professional background as detailed in the Data section. We report estimates that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$ using robust standard errors. The specification is detailed in its entirety in the Empirical Methodology Section.

TABLE A7: Earnings Regressions with Individual Traits

		Women		Men	
		× Self-emp		× Self-emp	
	Self-emp	-2.433 (1.780)		0.157 (0.860)	
Cognitives:	Quantitative GMAT	0.010*** (0.002)	0.029* (0.017)	0.009*** (0.001)	0.005 (0.007)
	Verbal GMAT	0.000 (0.002)	-0.029* (0.017)	0.001 (0.002)	0.010 (0.009)
Non-cognitives:	Communication	-0.018 (0.019)	0.006 (0.172)	-0.005 (0.016)	-0.030 (0.100)
	Work with diverse backgrounds	-0.023 (0.020)	-0.020 (0.195)	0.014 (0.016)	0.059 (0.094)
	Ability to organize	-0.040** (0.020)	0.069 (0.158)	-0.036** (0.016)	-0.010 (0.090)
	Capitalize on Change	-0.017 (0.018)	-0.138 (0.141)	-0.003 (0.016)	-0.263** (0.111)
	Delegate tasks	-0.019 (0.016)	-0.163 (0.158)	-0.035** (0.015)	0.181* (0.101)
	Adapt theory to practice	-0.012 (0.018)	0.319** (0.134)	0.004 (0.015)	0.025 (0.108)
	Understand other cultures	-0.010 (0.015)	0.065 (0.139)	-0.033** (0.013)	0.015 (0.068)
	Motivate others	0.026 (0.020)	-0.180 (0.148)	0.043*** (0.016)	-0.053 (0.098)
	Team player	0.064*** (0.021)	0.031 (0.166)	-0.002 (0.016)	-0.048 (0.101)
	Integrity	-0.021 (0.019)	0.216 (0.179)	-0.016 (0.015)	-0.012 (0.093)
	Initiative	0.077*** (0.021)	0.008 (0.201)	0.053*** (0.018)	-0.154 (0.111)
	Assertiveness	0.055*** (0.018)	-0.068 (0.215)	0.036** (0.016)	0.118 (0.099)
	Ethical standards	-0.039* (0.023)	0.298 (0.244)	-0.044** (0.017)	0.079 (0.100)
	Shrewdness	-0.022 (0.016)	-0.037 (0.135)	0.005 (0.013)	-0.109 (0.082)
	Physically attractive	0.040** (0.019)	-0.050 (0.170)	0.026 (0.017)	0.181* (0.092)
	Connections	0.015 (0.018)	0.061 (0.145)	0.046*** (0.014)	-0.003 (0.082)
Skill Balance:	Non-cognitives	0.273 (0.282)	-1.760 (2.724)	0.079 (0.226)	1.159 (1.098)
	Cognitives	0.026 (0.086)	-1.146 (0.824)	0.065 (0.078)	-0.337 (0.387)
Work-Life Balance:	Family	0.014 (0.029)	0.264 (0.355)	0.031 (0.028)	-0.280** (0.118)
	Career	-0.006 (0.022)	-0.272 (0.177)	0.007 (0.018)	0.173* (0.102)
	Wealth	-0.024 (0.027)	0.456* (0.271)	0.025 (0.022)	-0.158 (0.115)
Job Characteristics:	Interesting Work	0.075** (0.033)	0.588 (0.407)	0.039* (0.023)	0.064 (0.158)
	Authority	-0.028 (0.026)	-0.190 (0.345)	0.022 (0.020)	-0.423*** (0.120)
	Job security	-0.062*** (0.023)	-0.198 (0.195)	-0.078*** (0.019)	-0.048 (0.138)
	Compensation	0.078*** (0.024)	0.222 (0.205)	0.072*** (0.020)	0.247** (0.112)
	Challenging Work	0.074*** (0.023)	0.125 (0.192)	0.043** (0.019)	0.193 (0.123)
	No conflicting demands	-0.010 (0.027)	0.008 (0.234)	-0.043* (0.024)	0.108 (0.113)
	Hours	-0.036 (0.022)	-0.278 (0.244)	-0.021 (0.022)	-0.150 (0.139)
Observations		2,937		4,239	
R ²		0.373		0.401	

Notes: The table above reports coefficient estimates and standard errors (in parenthesis below) for regressions of the listed variables on the log of annual earnings as detailed in the Data section. The first two columns report estimates for women with the second of the two columns reporting the estimate for the stated variable interacted with a binary indicated for ever self-employed in waves II, III, or IV. The third and fourth columns repeat this for men. We do not report coefficients for control variables despite their inclusion. These variables include race/ethnicity, age, marriage status, presence of children under 18, family background, academic variables, and professional background as detailed in the Data Section. We report estimates that are statistically different from zero with * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$ using robust standard errors. The specification is detailed in its entirety in Empirical Methodology Section.