Jack- versus Jacqueline-of-all-trades? Self-Employment and Gender Differences in Skill Balance, Non-Cognitive Traits, and Preferences*

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Abstract

We compare the characteristics of highly educated, career-oriented female and male business professionals who are self-employed. Using a rich set of variables obtained from a longitudinal survey of individuals considering graduate management studies, we investigate gender differences in the roles of cognitive ability, non-cognitive traits, skill balance, and preferences for work-life balance and work characteristics in determining future self-employment outcomes. We find that the correlates of self-employed women differ from those pertaining to men. While higher non-cognitive traits and skill balance are associated with a higher probability of becoming self-employed for women, preferences over work-life balance and job characteristics are associated with a higher probability of self-employment for men. When analyzing the correlates of earnings by gender and employment status, we find that traditional employment rewards similar traits for both men and women. In contrast, self-employment rewards men and women differently: self-employed women receive an additional premium for their quantitative skills, while men with more balanced non-cognitive skills are rewarded. Interestingly, none of the traits nor the preferences associated with a higher probability of self-employment are associated with higher earnings for self-employed individuals.

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

Keywords: Gender differences; Self-employment; Non-cognitive skills; Skill balance.

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1 Introduction

According to Forbes' annual list of world billionaires, of a total of 2,640 billionaires in the planet, only 13% are women. Of all billionaires, the share of those who are self-made is 69%. Among women billionaires, however, this share is slightly less than 30% (Peterson-Withorn, 2024).[1]. In general, women have been shown to underperform men in business and financial occupations (Bertrand et al., 2010), which are among the highest paying occupations.(Bureau of Labor Statistics, 2024) This underperformance is often attributed to behavioral differences between men and women, such as risk attitudes, confidence, taste for competitive environments and ability to bargain. Most of these differences are based on experimental evidence (Azmat and Petrongolo, 2014; Croson and Gneezy, 2009), which may not always translate to actual work environments.

Self-employment is one such highly competitive male-dominated environment (Burke et al., 2002; Hipple and Hammond, 2016; Leoni and Falk, 2010; Verheul et al., 2012) where women implicitly "compete" against men. Start-ups possess significant profit-making potential, and now, more than ever, there is an increasing influx of women entering the start-up space. Especially in the current context, start-up survival may require changing business strategies or adopting innovative strategies, which is more likely to happen with highly confident entrepreneurs (Malmendier and Tate, 2015).

There is a large literature focusing on the main determinants of self-employment, such as demographic characteristics, family background, education, access to financial resources, among others (Blanchflower and Oswald, 1998; Dunn and Holtz-Eakin, 2000; Hundley, 2006; Evans and Leighton, 1990; Fairlie, 1999, 2004, 2005; Holtz-Eakin et al., 1994; Hout and Rosen, 2000; Lindquist et al., 2015). Others have studied the connection between self-employment and personality (Caliendo et al., 2014; Hamilton et al., 2019). Existing studies of the effects of non-cognitive (or "soft") skills on self-employment have either focused on men, or not accounted for potentially different results across gender (Uusitalo, 2001; Eren and Sula, 2012; Hartog et al., 2010; Aldén et al., 2017; Humphries, 2017; Levine and Rubinstein, 2017). Additionally, Lazear's theory of entrepreneurs as "Jacks of all trades" (Lazear, 2004, 2005) posits that those who are competent in a wide variety of skills have a comparative advantage in self-employment compared to traditional employment. This theory provides two specific predictions that we explore in this study, both of which have some empirical support but have yet to be studied differently by gender (Lazear, 2005; Silva, 2007; Hartog et al., 2010; Aldén et al., 2017). First, that those with more balanced skills will be more likely to self-select into self-employment, and second, that those with more balanced skills will be more successful in that role compared to those who are traditionally employed.

Aside from background and skills affecting self-employment, there is evidence suggesting that individual preferences may also be driving individuals into self-employment. For example, Hamilton (2000); Benz and Frey (2008); Blanchflower and Oswald (1998) and Hyytinen et al. (2013)

[1]"Self-made" refers to individuals who started their company as founders or co-founders, or established their own fortune (as opposed to inheriting it).

find that self-employed individuals earn less than paid workers. Other studies have investigated the role of non-cognitive traits on women who have self-selected into competitive environments that are male-dominated, where women compete mostly against men. Most of these studies, however, have focused on professional athletes or individuals who choose to enter certain competitive events, such as races or game shows.[2]

We study the relationship between self-employment outcomes and non-cognitive traits, cognitive skills, and preferences for work-life balance and job characteristics, and how these relationships differ by gender for a group of aspiring business professionals. We also investigate the role of skill balance in self-employment outcomes, testing the validity of Lazear's Jack-of-all-trades theory and exploring potential gender differences in the role of skill balance for this particular group. To provide insight into the roles of these characteristics in driving individuals into both traditional employment and self-employment, we investigate their correlation with earnings as a measure of success in each sector.

A challenge of studying self-employment in women is that, oftentimes, women are driven to self-employment not by the desire to maximize lifetime earnings or career satisfaction, but by other considerations, such as spending more time with their families or better work-life balance (Gurley-Calvez et al., 2009; Leoni and Falk, 2010; Özcan, 2011). These differences in preferences may lead to differences in early career work experience, human capital accumulation or educational attainment. Our objective, however, is to investigate the attributes of highly educated professionals with similar career ambitions, and how these attributes differ across men and women in their decision to become self-employed. We use the GMAT (Graduate Management Admission Test) registrant survey, which provides the advantage of including men and women with an interest in acquiring graduate education in business and management, signalling commitment to their careers.

The GMAT registrant survey was conducted in four waves between 1990 and 1998. In the first wave, registrants were administered a detailed questionnaire, where we obtain most of the variables of interest in our study along with a rich set of controls. Given the longitudinal nature of the survey, self-employment outcomes can be observed in the later waves of the survey. Additionally, our data offers several advantages not typically available to researchers studying characteristics of male and female workers in a given workplace, which we discuss in detail below.

First, the sample includes only men and women who registered to take the GMAT, which signals a certain level of interest in obtaining an MBA or related degree. Thus, our data contains a relatively homogeneous group in terms of commitment to their careers, interest in business, and prior accumulated human capital. Using a highly selected sample allows us to better understand gender differences in aspirations and decisions regarding self-employment, lessening the role of potentially confounding factors that would be magnified in a more diverse dataset.

Second, the survey data include several unique variables that may be related to self-employment

[2]Examples include tennis, e.g Jetter and Walker (2015), professional track and field athletics, e.g. Frick (2011), and professional chess, e.g. Gerdes and Gränsmark (2010).

outcomes. These include several measures of non-cognitive skills or characteristics deemed relevant for business, and preferences over work-life balance and job-related aspects. Additionally, the survey data are linked to GMAT registration and testing results, allowing us to measure cognitive ability in terms of an individual's quantitative and verbal skills.

We find that the factors associated with a higher probability of ever becoming self-employed differ between women and men. Specifically, women who exhibit higher levels of non-cognitive traits and lower quantitative skills are more likely to become self-employed. We also find some support for Lazear's Jack-of-all-trades theory of selection into self-employment, as women who have a more balanced portfolio of cognitive skills are more likely to become self-employed. Perhaps surprisingly, we find no patterns in terms of preferences over work-life balance and job attributes for women. In contrast, self-employed men do not exhibit any patterns in terms of skills or skill balance. Instead, preferences over work-life balance and job related characteristics are associated with a higher probability of self-employment for men: those who assign less importance to their careers, care less about working hours and job security, and place more value on doing work they consider interesting have a higher probability of being self-employed in the future.

In terms of earnings, we find that both traditional and self-employment reward similar traits in both men and women. Quantitative skills are associated with higher earnings for both men and women. Also, individuals who value doing interesting and challenging work, and those who place importance on compensation get rewarded, while those who seek out job security get penalized. Perhaps surprisingly, for both men and women, none of the traits and characteristics that yield higher earnings for the self-employed coincide with the factors that are associated with a higher probability of becoming self-employed. We find support for Lazear's Jack-of-all-trades theory of performance, as self-employed individuals who are balanced in terms of non-cognitive skills obtain higher earnings. However, this is the case only for men. We do not find evidence of skill balance correlating with earnings for women.

Our results contribute to the self-employment literature that explores the role of cognitive skills, non-cognitive traits and skill balance on self-employment. This is the first study to explicitly allow for gender differences in drivers of self-employment for a relatively homogeneous group in terms of professional aspirations. Existing studies use longitudinal US surveys such as the National Educational Longitudinal Study (NELS) and the National Longitudinal Survey of Youth 1979 - 2000 (NLSY) (Eren and Sula, 2012; Hartog et al., 2010; Levine and Rubinstein, 2017) that are more representative of the overall population, or data from other countries obtained from tests taken for compulsory military enlistment (Aldén et al., 2017; Uusitalo, 2001; Humphries, 2017). Most of these studies focus on men only, and those that include women in their data do not provide any insights specific to women (Hartog et al., 2010), other than the fact that they are less likely to become self-employed (Levine and Rubinstein, 2017). All studies find a positive relationship between higher levels of non-cognitive skills and selection into self-employment.[3]

[3]Eren and Sula (2012) use a composite of non-cognitive skills, while others use separate non-cognitive skills. Uusitalo (2001) uses dynamism, cautiousness and leadership, and Hartog et al. (2010); Levine and Rubinstein (2017) use

Results with respect to cognitive skills are mixed, with studies focusing on US samples showing a either a negative relationship (Eren and Sula, 2012; Hartog et al., 2010), or a positive effect for a specific subset of the sample (Levine and Rubinstein, 2017), and those focusing on other countries showing a positive relationship. Our findings are consistent with Eren and Sula (2012); Hartog et al. (2010), but only for self-employed women. In our sample of business professionals, selection of men into self-employment does not exhibit any of these patterns.

The closest in scope to our study are Hartog et al. (2010) and Aldén et al. (2017), who, aside from studying the role of skill balance on selection into self-employment, investigate the role of these traits in earnings for traditionally employed and self-employed. Like us, both studies evaluate skill balance in terms of "innate" characteristics rather than "acquired," and find some support for the Jack-of-all-trades theory. Our results further resemble Hartog et al. (2010) in terms of the discrepancy between determinants of self employment and those associated with a self-employment earnings premium, in contrast with Levine and Rubinstein (2017). However, none of these papers explore whether these roles differ by gender. Hartog et al. (2010) include women in the sample, but only allow for the level effect on self-employment and earnings to differ by gender, and Aldén et al. (2017) does not include women in the sample.

Regarding the role of non-pecuniary benefits to self-employment, using panel data from three European countries, Benz and Frey (2008) find a positive association between job satisfaction and self employment. They also find that women experience higher job satisfaction in general, but there is no specific result for self-employed women. Using a twins panel from Finland, Hyytinen et al. (2013) find that entrepreneurs earn less than salaried workers and work longer hours, but their work is less monotonous, they have more control over the pace and methods of their work, and have higher responsibility. Using the Panel Study of Entrepreneurial Dynamics (PSED) data on nascent entrepreneurs, Hurst and Pugsley (2011) find that a large fraction of entrepreneurs start their businesses for non-pecuniary reasons such as being their own boss, having more flexibility to choose their hours, or wanting to work from home, are less likely to want to grow, and are less likely to innovate. Our results for the men in our sample are consistent with these findings in terms of driving individuals into self-employment, and in terms of earnings for those who prioritize family or desire more authority in their job. We do not, however, find any evidence of importance of non-pecuniary benefits for self-employed women.

The rest of the paper proceeds as follows: in section 2, we describe our data sources and empirical strategy. Our results are presented in section 3. Finally, section 4 concludes and discusses our findings.

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social ability, locus of control, and self-esteem. Aldén et al. (2017) and Humphries (2017) use the results of an interview with a psychologist assessing emotional stability and ability to cope with stress.

2 Data and Empirical Methodology

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.

2.1 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.[4]

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 females and 2,072 males from the first survey wave.[5]

2.1.1 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

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

[5]Our definition of gender comes from self-reported responses from the GMAT registration file.

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.[6] 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.[7]

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.[8]

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 sores or that are missing

[6]The GMAT Registrant Survey occasionally asks respondents only about jobs where the respondent works 35 or more hours. In line with this, we consider full-time jobs to entail at least 35 hours in a typical work week.

[7]The startup failure rate is 90%, see Schroeder (2023).

[8]Earnings 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.

any of our explanatory variables of interest, we obtain 4,239 male observations, and 2,937 female observations.

2.1.2 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.[9] 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

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

gender earnings gap and evaluating job market outcomes (Grove et al., 2011; Chen et al., 2017).[10]

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). Given the gender focus of our study, we account for possible differences in broader preferences over family versus career. For this purpose, we include indicator variables reflecting whether individuals report that the following aspects of life are "very important:" family, career, and wealth.

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 varies across individuals and especially gender groups, and may have a different impact on the decision to be self-employed for each of these groups. 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."

[10] Cobb-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.

2.1.3 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-habitating 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.[11]

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.[12]

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 include a dummy variable for

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

[12] The 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.

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 at the time of each wave.

2.2 Descriptive Statistics

Descriptive statistics of each of our wave I covariates are shown in Table 1 separately for females and males 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 the male sample. 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, male scores are significantly higher only in traditional employment. 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 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 adapt theory to practice and 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. 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 are similar across gender for the self-employed. Both self-employed men and women report higher 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 differ by gender. 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 males is black, with higher proportions for black 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.

2.3 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.

2.3.1 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:

$$\Pr\left(SE_i = 1\right) = \Phi\big(\alpha + G_i\beta + N_i\delta + CV_i\lambda + P_i\mu + X_i\theta + \epsilon_i\big) \tag{1}$$

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 non-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.[13]

[13]In 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

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.

2.3.2 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:

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

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. [14] 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.

3 Results

In this section, we present the result of the empirical exercises described in Section 2. First, we present the determinants of eventual self-employment, followed by the correlates of earnings.

factors deemed important for success in business).

[14] Parents' level of education, undergraduate GPA and selectivity of undergraduate degree are not included in X_{iw}. Due 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.

3.1 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 by gender.

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.

3.2 Earnings

In terms of earnings, the results of our analysis, presented in Table 3, reveal similar factors being rewarded across genders 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 traits like ethics and teamwork appear to incur a penalty for both men and women.

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.

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.

4 Discussion and Conclusion

This study explores gender differences in the factors influencing the likelihood of individuals becoming self-employed and their earnings. 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 deprioritizing their career, and preferences over job related characteristics such as valuing interesting work or job security.

Regarding earnings, both genders 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. For the self-employed, the characteristics of those who earn more differ by gender. 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.

Our findings offer partial support for Lazear's Jack-of-all-trades theory, with each gender satisfying only one of the predictions stemming from this theory. While being a "Jacqueline-of-all-trades" is associated with self-selection into self-employment for women, that is not the case for men. In contrast, being a Jack-of-all-trades is associated with higher earnings for men, but not for women. 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 to study 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 are male-dominated and women compete against 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 across genders. These differences may be consistent with traditional gender stereotypes, 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 drivers and 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. According 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. 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 what many might consider to be gender stereotypes (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-owned businesses should account for potential gender differences in both the drivers into self-employment and the traits that are rewarded once self-employed.

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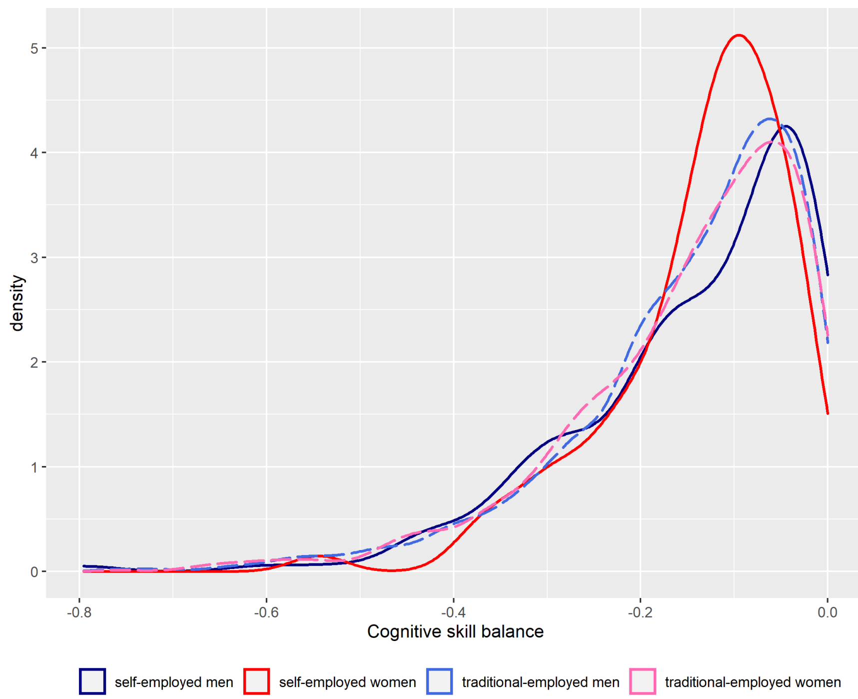

FIGURE 1: Kernel Densities of Cognitive Skill Balance, by gender and employment

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 Section 2.1. The variable takes a max value of zero for the most balanced and declines as the cognitive skills are less balanced.

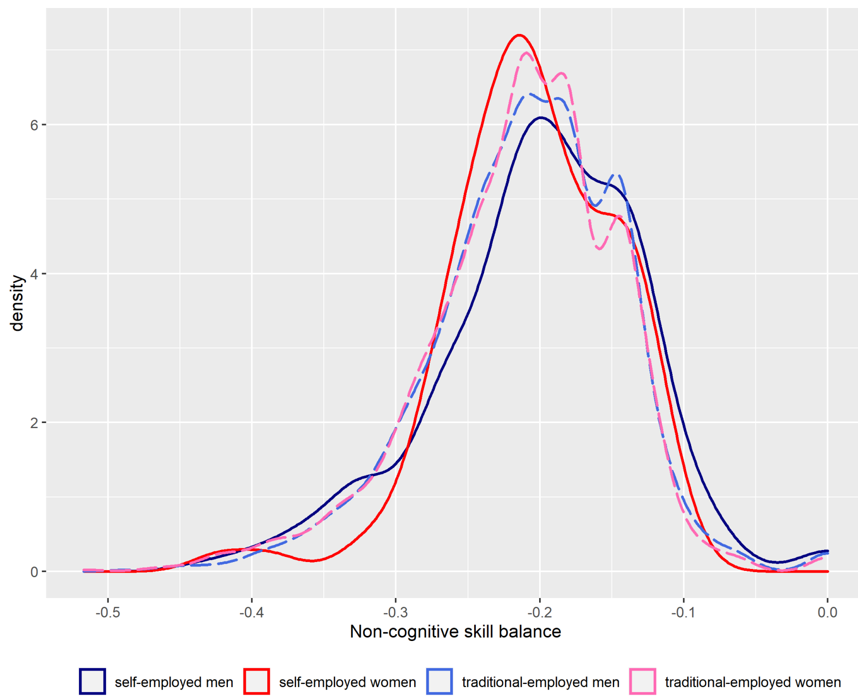

FIGURE 2: Kernel Densities of Non-Cognitive Skill Balance, by gender and employment

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 Section 2.1. The variable takes a max value of zero for the most balanced and declines as the non-cognitive skills are less balanced.

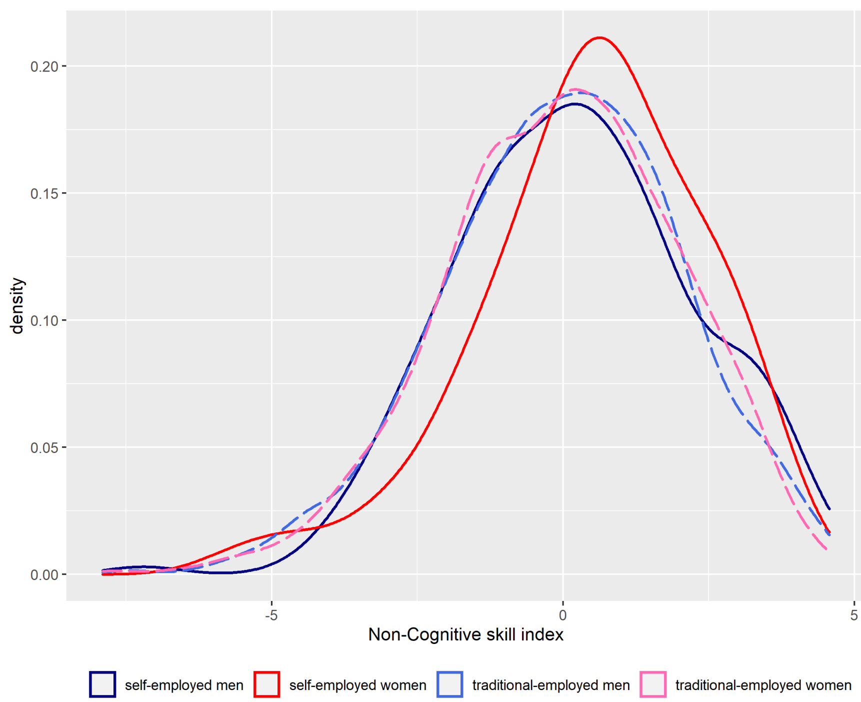

FIGURE 3: Kernel Densities of Non-Cognitive Skill Index, by gender and employment

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 Section 2.1. The variable is mean zero and standard deviation of one within each gender.

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

Variable	Female		Male		Employment differences (Trad - Self)		Gender differences (Male - Female)	
	Self emp	Trad emp	Self emp	Trad emp	Female	Male	Self emp	Trad emp
Cognitives								
Quantitative GMAT	25.77	26.65	30.87	31.07	0.88	0.20	5.10***	4.42***
	(7.67)	(8.01)	(7.70)	(8.58)				
Verbal GMAT	28.00	27.70	28.72	29.13	–0.30	0.41	0.72	1.43***
	(8.76)	(7.74)	(7.87)	(7.78)				
Non-cognitives								
Index	0.47	–0.03	0.20	–0.02	–0.50**	–0.22	–0.27	0.01
	(1.96)	(2.00)	(2.03)	(2.03)				
Skill Balance								
Non-cognitives	–0.21	–0.21	–0.20	–0.21	–0.01	–0.01*	0.01	0.00
	(0.06)	(0.07)	(0.07)	(0.07)				
Cognitives	–0.14	–0.15	–0.14	–0.15	–0.01	–0.01	–0.00	0.00
	(0.10)	(0.13)	(0.13)	(0.12)				
Work-Life Balance								
Family	0.89	0.88	0.89	0.88	–0.01	–0.02	0.00	–0.01
	(0.31)	(0.32)	(0.31)	(0.33)				
Career	0.71	0.69	0.57	0.61	–0.03	0.05	–0.15**	–0.07***
	(0.45)	(0.46)	(0.50)	(0.49)				
Wealth	0.18	0.18	0.24	0.25	0.00	0.02	0.06	0.08***
	(0.38)	(0.38)	(0.43)	(0.44)				
Job Preferences								
Interesting Work	0.87	0.90	0.89	0.85	0.04	–0.04*	0.02	–0.06***
	(0.34)	(0.30)	(0.32)	(0.36)				
Authority	0.81	0.78	0.69	0.72	–0.04	0.03	–0.12**	–0.06***
	(0.39)	(0.42)	(0.46)	(0.45)				
Job security	0.53	0.58	0.38	0.48	0.05	0.09***	–0.14**	–0.10***
	(0.50)	(0.49)	(0.49)	(0.50)				
Compensation	0.63	0.68	0.60	0.63	0.05	0.04	–0.03	–0.04**
	(0.49)	(0.47)	(0.49)	(0.48)				
Challenging Work	0.33	0.31	0.27	0.29	–0.02	0.01	–0.06	–0.02
	(0.47)	(0.46)	(0.45)	(0.45)				
No conflicting demands	0.23	0.21	0.19	0.18	–0.02	–0.01	–0.04	–0.04***
	(0.42)	(0.41)	(0.39)	(0.38)				
Hours	0.32	0.37	0.18	0.24	0.05	0.05*	–0.14**	–0.13***
	(0.47)	(0.48)	(0.39)	(0.43)				
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 by gender 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 females, then males, and then comparing gender differences (male minus female) 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 Section 2.

Table 2: Probit Marginal Effect Estimates for Predictors of Eventual Self-employment, by Gender

		Female	Male
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 Section 2.1. The first column reports estimates for female respondents and the second column for male respondents 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 Section 2.1. 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 Section 2.3.

TABLE 3: Earnings Regressions for $\log(\text{Salary})$, by gender

		Female		Male	
			× Self-emp		× Self-emp
	Self-emp	-0.512		0.097	
		(0.561)		(0.378)	
Cognitives:	Quantitative GMAT	0.012***	0.025*	0.011***	0.003
		(0.002)	(0.013)	(0.001)	(0.008)
	Verbal GMAT	0.000	-0.024	0.002	0.010
		(0.002)	(0.015)	(0.002)	(0.009)
Non-cognitives:	Index	0.013*	0.011	0.009	-0.031
		(0.007)	(0.052)	(0.006)	(0.032)
Skill Balance:	Non-cognitives	0.016	0.420	0.237	1.487*
		(0.207)	(1.798)	(0.181)	(0.873)
	Cognitives	0.055	-0.764	0.050	-0.183
		(0.087)	(0.734)	(0.079)	(0.399)
Work-Life Balance:	Family	0.040	0.062	0.029	-0.164
		(0.029)	(0.228)	(0.028)	(0.113)
	Career	0.000	-0.201	0.013	0.132
		(0.022)	(0.174)	(0.019)	(0.099)
	Wealth	-0.017	0.447*	0.044**	-0.152
		(0.028)	(0.237)	(0.022)	(0.122)
Job Characteristics:	Interesting Work	0.082**	0.419	0.054**	0.056
		(0.034)	(0.366)	(0.023)	(0.166)
	Authority	-0.034	0.178	0.027	-0.338***
		(0.027)	(0.307)	(0.021)	(0.124)
	Job security	-0.060**	-0.319	-0.094***	0.043
		(0.024)	(0.225)	(0.019)	(0.121)
	Compensation	0.087***	0.246	0.079***	0.176
		(0.024)	(0.263)	(0.020)	(0.118)
	Challenging Work	0.082***	0.005	0.051***	0.139
		(0.023)	(0.195)	(0.020)	(0.114)
	No conflicting demands	-0.010	0.068	-0.044*	0.149
		(0.028)	(0.257)	(0.024)	(0.119)
	Hours	-0.041*	-0.179	-0.027	-0.155
		(0.023)	(0.253)	(0.023)	(0.147)
Observations		2,937		4,239	
R^2		0.340		0.369	

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 Section 2.1. The first two columns report estimates for female respondents 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 male respondents. 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 Section 2.1. 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 Section 2.3.

1

1 Appendix Tables

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

	Female		Male		Employment differences (Trad - Self)		Gender differences (Male - Female)	
Variable	Self emp	Trad emp	Self emp	Trad emp	Female	Male	Self emp	Trad emp
Non-cognitives								
Communication	3.49	3.42	3.36	3.33	–0.07	–0.03	–0.14*	–0.10***
	(0.58)	(0.59)	(0.63)	(0.62)				
Work with diverse backgrounds	3.65	3.65	3.55	3.59	0.01	0.04	–0.10	–0.07***
	(0.50)	(0.55)	(0.55)	(0.58)				
Ability to organize	3.59	3.61	3.41	3.43	0.02	0.02	–0.18**	–0.18***
	(0.60)	(0.56)	(0.63)	(0.63)				
Capitalize on Change	3.31	3.16	3.28	3.19	–0.15**	–0.09**	–0.03	0.03
	(0.64)	(0.65)	(0.61)	(0.66)				
Delegate tasks	3.41	3.23	3.34	3.25	–0.18**	–0.09**	–0.07	0.02
	(0.63)	(0.70)	(0.62)	(0.69)				
Adapt theory to practice	3.13	3.13	3.27	3.20	–0.00	–0.07	0.14	0.07***
	(0.79)	(0.67)	(0.61)	(0.68)				
Understand other cultures	2.81	2.55	2.77	2.60	–0.26***	–0.17***	–0.05	0.05
	(0.87)	(0.86)	(0.88)	(0.89)				
Motivate others	3.45	3.32	3.28	3.27	–0.13*	–0.01	–0.17**	–0.04**
	(0.65)	(0.62)	(0.65)	(0.65)				
Team player	3.56	3.65	3.52	3.58	0.09	0.06	–0.04	–0.07***
	(0.64)	(0.57)	(0.60)	(0.61)				
Integrity	3.47	3.35	3.38	3.31	–0.12*	–0.07	–0.09	–0.05**
	(0.62)	(0.63)	(0.64)	(0.64)				
Initiative	3.71	3.61	3.63	3.56	–0.11*	–0.07*	–0.09	–0.04**
	(0.50)	(0.52)	(0.51)	(0.53)				
Assertiveness	3.43	3.20	3.18	3.16	–0.23***	–0.02	–0.25***	–0.04
	(0.56)	(0.64)	(0.65)	(0.66)				
Ethical standards	3.82	3.76	3.66	3.64	–0.06	–0.03	–0.16***	–0.12***
	(0.41)	(0.46)	(0.59)	(0.54)				
Shrewdness	2.60	2.62	2.82	2.78	0.02	–0.05	0.22**	0.15***
	(0.66)	(0.76)	(0.79)	(0.74)				
Physically attractive	3.09	3.13	3.02	3.03	0.04	0.00	–0.06	–0.10***
	(0.59)	(0.57)	(0.61)	(0.59)				
Connections	2.57	2.54	2.59	2.58	–0.03	–0.02	0.02	0.04
	(0.78)	(0.76)	(0.88)	(0.77)				
Demographics								
Asian	0.18	0.15	0.17	0.15	–0.03	–0.02	–0.00	0.00
	(0.38)	(0.35)	(0.38)	(0.36)				
Black	0.14	0.17	0.05	0.08	0.02	0.04**	–0.10**	–0.08***
	(0.35)	(0.37)	(0.21)	(0.28)				
Hispanic	0.14	0.16	0.19	0.16	0.02	–0.03	0.05	0.00
	(0.35)	(0.37)	(0.40)	(0.37)				
Married	0.31	0.30	0.41	0.38	–0.01	–0.03	0.11*	0.08***
	(0.46)	(0.46)	(0.49)	(0.49)				
Has children	0.20	0.12	0.24	0.19	–0.07*	–0.05*	0.04	0.06***
	(0.40)	(0.33)	(0.43)	(0.39)				
Age	28.84	26.62	28.85	27.66	–2.22***	–1.19**	0.01	1.04***
	(6.95)	(5.42)	(7.00)	(5.78)				
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 by gender 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 females, then males, and then comparing gender differences (male minus female) 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 Section 2.

TABLE A2: Probit Marginal Effect Estimates for Predictors of Eventual Self-employment, by Gender

		Female	Male
Cognitives:	Quantitative GMAT	-0.002*	0.000
		(0.001)	(0.001)
	Verbal GMAT	0.002	-0.002*
		(0.001)	(0.001)
Non-cognitives:	Communication	0.001	0.006
		(0.011)	(0.012)
	Work with diverse backgrounds	-0.011	-0.022*
		(0.011)	(0.012)
	Ability to organize	-0.001	-0.010
		(0.011)	(0.011)
	Capitalize on Change	0.005	0.013
		(0.011)	(0.012)
	Delegate tasks	0.019*	0.017
		(0.011)	(0.011)
	Adapt theory to practice	-0.025**	0.001
		(0.011)	(0.011)
	Understand other cultures	0.016**	0.011
		(0.008)	(0.009)
	Motivate others	0.023*	-0.012
		(0.012)	(0.011)
	Team player	-0.024**	-0.003
		(0.011)	(0.011)
	Integrity	0.003	0.007
		(0.011)	(0.012)
	Initiative	0.008	0.022
		(0.014)	(0.014)
	Assertiveness	0.033***	-0.002
		(0.011)	(0.012)
	Ethical standards	0.027*	0.002
		(0.015)	(0.013)
	Shrewdness	-0.009	0.006
		(0.010)	(0.010)
	Physically attractive	-0.003	0.005
		(0.011)	(0.012)
	Connections	-0.007	-0.011
		(0.011)	(0.011)
Skill Balance:	Non-cognitives	-0.015	0.091
		(0.168)	(0.176)
	Cognitives	0.113**	0.087
		(0.051)	(0.060)
Work-Life Balance:	Family	0.007	0.016
		(0.020)	(0.021)
	Career	-0.001	-0.032**
		(0.014)	(0.014)
	Wealth	-0.001	0.001
		(0.016)	(0.017)
Job Characteristics:	Interesting Work	-0.028	0.040**
		(0.019)	(0.020)
	Authority	0.002	-0.023
		(0.016)	(0.016)
	Job security	0.000	-0.025*
		(0.013)	(0.015)
	Compensation	-0.021	-0.005
		(0.013)	(0.014)
	Challenging Work	-0.005	-0.002
		(0.014)	(0.015)
	No conflicting demands	0.006	0.027
		(0.015)	(0.018)
	Hours	-0.007	-0.028
		(0.014)	(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 Section 2.1. The first column reports estimates for female respondents and the second column for male respondents 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 Section 2.1. 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 Section 2.3.

TABLE A3: Probit Estimates for Predictors of Eventual Self-employment, by Gender

		Female	Male
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 Section 2.1. The first column reports estimates for female respondents and the second column for male respondents 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 Section 2.1. 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 Section 2.3.

Table A4: Probit Estimates for Predictors of Eventual Self-employment, by Gender

		Female	Male
Cognitives:	Quantitative GMAT	-0.021*	0.001
		(0.011)	(0.007)
	Verbal GMAT	0.015	-0.014*
		(0.011)	(0.008)
Non-cognitives:	Communication	0.007	0.039
		(0.102)	(0.074)
	Work with diverse backgrounds	-0.105	-0.134*
		(0.105)	(0.072)
	Ability to organize	-0.007	-0.063
		(0.101)	(0.069)
	Capitalize on Change	0.044	0.078
		(0.100)	(0.076)
	Delegate tasks	0.179*	0.104
		(0.096)	(0.070)
	Adapt theory to practice	-0.229**	0.004
		(0.103)	(0.068)
	Understand other cultures	0.151**	0.068
		(0.075)	(0.058)
	Motivate others	0.207*	-0.073
		(0.113)	(0.071)
	Team player	-0.218**	-0.021
		(0.102)	(0.066)
	Integrity	0.025	0.041
		(0.104)	(0.072)
	Initiative	0.070	0.137
		(0.132)	(0.088)
	Assertiveness	0.306***	-0.010
		(0.098)	(0.076)
	Ethical standards	0.248*	0.013
		(0.139)	(0.080)
	Shrewdness	-0.079	0.039
		(0.087)	(0.065)
	Physically attractive	-0.031	0.032
		(0.102)	(0.077)
	Connections	-0.068	-0.067
		(0.099)	(0.069)
Skill Balance:	Non-cognitives	-0.136	0.567
		(1.543)	(1.093)
	Cognitives	1.040**	0.541
		(0.468)	(0.373)
Work-Life Balance:	Family	0.066	0.097
		(0.181)	(0.129)
	Career	-0.011	-0.196**
		(0.125)	(0.086)
	Wealth	-0.013	0.009
		(0.145)	(0.103)
Job Characteristics:	Interesting Work	-0.255	0.247**
		(0.176)	(0.122)
	Authority	0.018	-0.143
		(0.146)	(0.099)
	Job security	0.003	-0.157*
		(0.119)	(0.091)
	Compensation	-0.191	-0.034
		(0.121)	(0.090)
	Challenging Work	-0.049	-0.010
		(0.127)	(0.093)
	No conflicting demands	0.055	0.168
		(0.142)	(0.112)
	Hours	-0.063	-0.176
		(0.132)	(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 Section 2.1. The first column reports estimates for female respondents and the second column for male respondents 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 Section 2.1. 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 Section 2.3.

TABLE A5: Linear Probability Model Estimates for Predictors of Eventual Self-employment, by Gender

		Female	Male
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 Section 2.1. The first column reports estimates for female respondents and the second column for male respondents 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 Section 2.1. 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 Section 2.3.

TABLE A6: Linear Probability Model Estimates for Predictors of Eventual Self-employment, by Gender

		Female	Male
Cognitives:	Quantitative GMAT	-0.002	0.000
		(0.001)	(0.001)
	Verbal GMAT	0.002	-0.002
		(0.001)	(0.001)
Non-cognitives:	Communication	-0.000	0.007
		(0.011)	(0.012)
	Work with diverse backgrounds	-0.008	-0.021*
		(0.012)	(0.012)
	Ability to organize	-0.004	-0.010
		(0.012)	(0.011)
	Capitalize on Change	0.007	0.012
		(0.012)	(0.012)
	Delegate tasks	0.018	0.016
		(0.011)	(0.011)
	Adapt theory to practice	-0.025*	0.000
		(0.013)	(0.011)
	Understand other cultures	0.020**	0.011
		(0.010)	(0.010)
	Motivate others	0.020	-0.012
		(0.013)	(0.012)
	Team player	-0.022	-0.004
		(0.013)	(0.011)
	Integrity	0.008	0.006
		(0.012)	(0.011)
	Initiative	0.010	0.021
		(0.013)	(0.014)
	Assertiveness	0.031***	-0.003
		(0.011)	(0.013)
	Ethical standards	0.022	0.002
		(0.014)	(0.013)
	Shrewdness	-0.004	0.006
		(0.009)	(0.011)
	Physically attractive	-0.000	0.007
		(0.012)	(0.013)
	Connections	-0.002	-0.009
		(0.012)	(0.011)
Skill Balance:	Non-cognitives	-0.152	0.073
		(0.176)	(0.186)
	Cognitives	0.102**	0.091
		(0.048)	(0.059)
Work-Life Balance:	Family	0.006	0.013
		(0.020)	(0.020)
	Career	-0.002	-0.029**
		(0.014)	(0.015)
	Wealth	0.002	0.000
		(0.017)	(0.017)
Job Characteristics:	Interesting Work	-0.035	0.037**
		(0.024)	(0.018)
	Authority	0.003	-0.022
		(0.016)	(0.017)
	Job security	-0.003	-0.025*
		(0.014)	(0.015)
	Compensation	-0.019	-0.002
		(0.014)	(0.015)
	Challenging Work	-0.003	-0.000
		(0.016)	(0.015)
	No conflicting demands	0.003	0.028
		(0.017)	(0.019)
	Hours	-0.009	-0.028*
		(0.015)	(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 Section 2.1. The first column reports estimates for female respondents and the second column for male respondents 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 Section 2.1. 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 Section 2.3.

TABLE A7: Earnings Regressions for $\log(\text{Salary})$, by gender

		Female	$\times$ Self-emp	Male	$\times$ Self-emp
	Self-emp	-2.274		0.073	
		(1.791)		(0.875)	
Cognitives:	Quantitative GMAT	0.012***	0.029*	0.011***	0.005
		(0.002)	(0.017)	(0.001)	(0.007)
	Verbal GMAT	0.002	-0.030*	0.003	0.010
		(0.002)	(0.017)	(0.002)	(0.009)
Non-cognitives:	Communication	-0.016	-0.000	-0.004	-0.018
		(0.019)	(0.172)	(0.016)	(0.101)
	Work with diverse backgrounds	-0.020	0.007	0.016	0.067
		(0.019)	(0.196)	(0.016)	(0.094)
	Ability to organize	-0.038*	0.063	-0.027*	-0.009
		(0.020)	(0.157)	(0.016)	(0.090)
	Capitalize on Change	-0.020	-0.124	-0.003	-0.253**
		(0.019)	(0.142)	(0.016)	(0.109)
	Delegate tasks	-0.019	-0.181	-0.035**	0.181*
		(0.016)	(0.160)	(0.015)	(0.102)
	Adapt theory to practice	-0.015	0.319**	0.002	0.019
		(0.018)	(0.135)	(0.015)	(0.107)
	Understand other cultures	-0.007	0.035	-0.031**	0.021
		(0.015)	(0.141)	(0.013)	(0.068)
	Motivate others	0.027	-0.167	0.047***	-0.048
		(0.021)	(0.149)	(0.016)	(0.097)
	Team player	0.064***	0.005	-0.007	-0.049
		(0.022)	(0.166)	(0.016)	(0.101)
	Integrity	-0.016	0.193	-0.020	-0.003
		(0.019)	(0.180)	(0.015)	(0.092)
	Initiative	0.082***	0.017	0.058***	-0.158
		(0.021)	(0.199)	(0.019)	(0.110)
	Assertiveness	0.052***	-0.065	0.034**	0.110
		(0.018)	(0.214)	(0.017)	(0.099)
	Ethical standards	-0.039*	0.309	-0.043**	0.074
		(0.023)	(0.240)	(0.017)	(0.101)
	Shrewdness	-0.019	-0.028	0.005	-0.123
		(0.016)	(0.136)	(0.013)	(0.083)
	Physically attractive	0.043**	-0.067	0.025	0.184**
		(0.019)	(0.170)	(0.017)	(0.092)
	Connections	0.015	0.062	0.044***	-0.008
		(0.018)	(0.145)	(0.014)	(0.083)
Skill Balance:	Non-cognitives	0.234	-1.557	0.123	1.069
		(0.283)	(2.746)	(0.227)	(1.121)
	Cognitives	0.027	-1.219	0.040	-0.321
		(0.087)	(0.818)	(0.078)	(0.386)
Work-Life Balance:	Family	0.018	0.265	0.038	-0.245**
		(0.029)	(0.354)	(0.028)	(0.116)
	Career	-0.008	-0.272	0.006	0.182*
		(0.022)	(0.179)	(0.018)	(0.102)
	Wealth	-0.023	0.492*	0.029	-0.159
		(0.028)	(0.273)	(0.022)	(0.115)
Job Characteristics:	Interesting Work	0.075**	0.586	0.050**	0.054
		(0.034)	(0.401)	(0.023)	(0.158)
	Authority	-0.029	-0.166	0.027	-0.418***
		(0.026)	(0.341)	(0.021)	(0.121)
	Job security	-0.063***	-0.224	-0.085***	-0.040
		(0.023)	(0.194)	(0.019)	(0.136)
	Compensation	0.079***	0.239	0.078***	0.239**
		(0.024)	(0.204)	(0.020)	(0.111)
	Challenging Work	0.081***	0.104	0.044**	0.198
		(0.023)	(0.193)	(0.020)	(0.121)
	No conflicting demands	-0.017	0.009	-0.048**	0.106
		(0.027)	(0.235)	(0.024)	(0.111)
	Hours	-0.032	-0.266	-0.019	-0.147
		(0.023)	(0.245)	(0.022)	(0.138)
Observations		2,937		4,239	
R^2		0.368		0.391	

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 Section 2.1. The first two columns report estimates for female respondents 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 male respondents. 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 Section 2.1. 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 Section 2.3.