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Transitions to Entrepreneurship and Industry-Specific Barriers

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ABSTRACT

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Drivers of entrepreneurial entry are investigated in this study by examining how entry into small-business ownership is shaped by industry-specific constraints. The human- and financial-capital endowments of potential entrepreneurs entering firms in various industries are shown to differ profoundly, depending on the type of venture entered. The educational credentials of highly educated potential entrepreneurs, in particular, predict avoidance of small-firm ownership in some industries as well as attraction to others. Recognizing that individuals choose an industry sector jointly with their decision to enter entrepreneurship, we find that the conventional practice of conflating different industry types in empirical analyses of transitions to entrepreneurship generates misleading findings about the determinants of entrepreneurship.

JEL Classification: J24, L26, M13

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1. Introduction

Researchers as well as policy-makers are interested in the determinants of entrepreneurial entry. New firm creation appears to enhance an economy's productivity, intensify market competition, and promote economic growth (Audretsch et al., 2006; Foster et al., 2008). Governments the world over have implemented a suite of policies designed to stimulate entrepreneurship. Governments often seek to target these programs effectively in order to utilize their scarce resources efficiently. To this end, it is necessary to obtain an accurate understanding of the determinants of entrepreneurial entry.

A large literature now explains why some individuals are more likely than others to become entrepreneurs (Parker, 2009). Available evidence is primarily derived from econometric models of discrete occupational choice, where self employment or business ownership is commonly identified with the entrepreneurial occupation. An implicit assumption underlying this type of analysis is homogeneity of the entrepreneurial occupational category. Thus, researchers typically treat all entries as though the human and financial endowments of potential entrepreneurs facilitating successful entry are identical in different industry sectors.

In fact, the self-employed are indisputably an unusually diverse group, ranging from casual labourers at one end of the spectrum to highly educated and specialized professionals at the other. The human- and financial-capital requirements facilitating successful entry are not homogeneous across industry types. Rather, the determinants of entry vary across industries requiring little in the way of advanced academic credentials and/or large investments of financial capital, as opposed to fields where potential entrepreneurs need substantial endowments of both. Simply stated, entry barriers are higher in some industries than in others. Similarly, applicable opportunity costs incurred by entrants vary substantially across industry sectors. Research to date, nonetheless, has scarcely recognised the heterogeneity of industry requirements and has instead combined disparate industry types when studying the entry process.

This study investigates whether the practice of aggregating across different industry types matters in terms of understanding the determinants of entrepreneurial entry. Using data from 1996 and 2001 panels of the U.S. Census Bureau's Survey of Income and Program Participation (SIPP), we find that it does. Recognizing heterogeneity in business ownership requirements across industry groups, we employ a classification of firms by financial- and human-capital intensiveness, or entry barriers. Our guiding hypothesis is that industry context shapes impacts of entrepreneur resource endowments on small-firm entry patterns. We utilize the concept of high- and low-barrier industry subgroups to demonstrate that determinants of entry differ sharply across sectors.

Because individuals choose their industry sector jointly with their decision to enter, we adopt a multi-pronged estimation strategy. First, we analyse entry into small-business ownership utilizing a conventional "aggregated" analysis of entry; we then estimate a multinomial probit model with three outcomes: 1) entry into a low-barrier industry; 2) entry into a high-barrier industry; 3) no entry. Next, we analyse entry choices of high- or low-barrier industries in a bivariate sample selection model. Our findings exhibit a high degree of consistency, indicating that potential entrepreneurs tend to self-select into certain industries, depending upon their initial resource endowments. Consistent with opportunity cost considerations, those with advanced educational credentials commonly avoid fields where owner remuneration is low, on average, and are attracted to industries where expected returns are high. These facts suggest that the conventional approach of conflating different industry types in empirical analyses of transitions to entrepreneurship generates misleading findings about the determinants of entrepreneurial entry.

Our study has the following structure. The next section draws on background literature germane to our enquiry. The section after describes the data used in our analyses. We then present and discuss the empirical strategy and findings and provide an extensive sensitivity analysis. The analysis concludes with a summary of the main findings, policy implications, limitations, and suggestions for future research.

2. Background Literature

According to a recent overview of the literature, most individual-level studies of entry (a) emphasise the roles of potential entrepreneur human capital, financial capital, demographic, household, and labour-market factors; and (b) treat entrepreneurs as a homogenous group in terms of the industry sectors they enter (Parker, 2009). There are but a few exceptions to this overall pattern, with some scholars suggesting that entrepreneurs lacking human and financial capital are more likely to enter service rather than manufacturing industries because entry barriers and minimum efficient scales are lower in the former than in the latter – making sustainable entry easier (Bhide, 2000; Arauzo-Carod and Segarra-Blasco, 2005; van Stel et al., 2007). Utilizing a complementary approach, Bates (1995, 1997), analyzing SIPP data, has reported positive and significant effects of formal education on the probability of entering self-employment in skilled services, as well as negative, significant effects on the probability of self-employment entry in construction. Bates' findings are important because they hint at reasons why the literature has failed to reach agreement about the effects of owner factor endowments on entrepreneurial entry. In their investigation into low Hispanic self-employment rates, Lofstrom and Wang (2009) have found that a classification of firms by entry barriers is effective in explaining differences in entrepreneurship across ethnic groups. However, we know of no thorough, general and direct analysis of this proposition.

Irrespective of degree of aggregation across industry groups, the above studies are broadly consistent with a large body of literature indicating that the people most likely to enter self employment and small-business ownership have higher personal net worth and stronger human-capital credentials than non-entrants. Similarly, increased success and survival odds typify well-capitalized small businesses run by owners having the human capital (education, experience, expertise) appropriate for operating viable ventures (see, for example, Dunn and Holtz-Eakin, 2000; Evans and Jovanovic, 1989; Bates, 1990; Cooper et al., 1994; Fairlie and Robb, 2008; Hout and Rosen, 2000). Nonetheless, substantial controversy remains.

Causal links between human-capital endowments of potential entrepreneurs and entry into firm ownership are disputed, both on theoretical and empirical grounds. Possessing advanced educational credentials may impact entry into entrepreneurship in off-setting ways. On the negative side, greater education increases options in paid-employment, thereby increasing the opportunity costs of pursuing entrepreneurship. On the positive side, formal education often enhances one's analytical abilities, communication skills, provides specific skills needed to run certain types of ventures (accounting, engineering, etc.), and promotes understanding of markets and entrepreneurial processes. Another possibility is that the knowledge and skills gained from formal education may be unnecessary for starting a business, yet a positive relationship with entry may still prevail, if education attainment serves as a proxy for ambition, endurance, and social background (Parker, 2009).

Thus, a recent meta-analysis by van der Sluis et al. (2008) failed to find a clear, positive relationship between entry and the educational backgrounds of potential entrepreneurs, although studies examining entrepreneurship entry in the Americas often did report such positive relationships. These results are broadly consistent with findings that advanced educational credentials draw potential entrepreneurs toward some industries and away from others (Bates, 1995, 1997). In such situations, an inappropriate degree of aggregation across dissimilar industries may explain why "there is no evidence of a systematic relationship between an individual's schooling level and the probability of selection into entrepreneurship" (van der Sluis et al., 2008, p. 817). Specifically, we expect higher levels of formal education to promote entry into high-barrier industries because education provides more than useful skills; advanced credentials can also be leveraged to obtain and marshal resources necessary for successful venture operation (Parker and van Praag, 2006; Bates, 1990). Yet, this outcome is uncertain precisely because highly educated individuals often face higher opportunity costs of leaving paid employment for entrepreneurship. If they enter at all, they are therefore more likely to do so in high-barrier industries where the expected payoffs exceed those in low-barrier industries.

Commencing with Evans and Jovanovic (1989), numerous studies have concluded that one's propensity to enter into entrepreneurship is shaped by personal wealth levels. Evans and Jovanovic argue that greater wealth facilitates entry because borrowing constraints often bind. For those with sufficient wealth to avoid borrowing constraints, Evans and Jovanovic predict unimpeded entry; when constraints were binding, entrepreneurial ambitions will often be frustrated. Further, they note that unobserved heterogeneity could engender a spurious correlation between net assets and entry, even in cases where individuals faced no borrowing constraints. Thus began a long controversy about whether findings of positive relationships between wealth holdings and entrepreneurship truly reflect borrowing constraints.

Although Evans and Jovanovic (1989) did not address the question of why potential entrepreneurs were credit constrained, others have shown how various information asymmetries limit the ability of financial intermediaries to evaluate new-firm projects effectively (see, for example, Stiglitz and Weiss, 1981; Banerjee and Newman, 1993; Aghion and Bolton, 1997). A model proposed by Aghion and Bolton (1997) demonstrates that moral hazard problems tend to be most acute at low wealth levels; poorer entrepreneurs may rationally choose to supply insufficient effort to their investment projects. This possibility encourages financial intermediaries to adopt asset-based lending policies, denying loans to prospective borrowers who lack collateral to offset moral hazard concerns.

Studies suggesting that borrowing constraints are unlikely to restrict potential entrepreneurs proceed not by denying information asymmetry issues, but by challenging the empirical finding that higher wealth predicts entry. The direction of causation could plausibly run in the opposite direction. At least two sources of endogeneity are possible. First, if highly capable individuals are above-average earners and savers and are also disproportionately inclined to enter entrepreneurship, an observed correlation between wealth levels and entrepreneurship may reflect this unobserved trait, quite irrespective of borrowing constraints. Second, wealthier people may simply have a greater preference for being entrepreneurs than the less wealthy. Hurst and Lusardi (2004) observe that the relationship between entrepreneurial entry and wealth appears to be flat up to the high end of the wealth distribution: “It is only at the top of the wealth distribution – after the 95th percentile, that a positive relationship can be found” (p. 319).

Although it is not entirely clear what explains this finding, they conclude that borrowing constraints do not look like a promising candidate.

Holtz-Eakin et al. (1994) and others sought to overcome endogeneity problems by analyzing impacts of windfalls and inheritances on the probability of subsequent entrepreneurial entry. Yet, inheritance recipients are not a random cross section of the population; many are attached to wealthy and successful families as well as powerful social networks. Advantageous connections can convey advantages facilitating successful entry into entrepreneurship, including the ability to borrow start-up capital from family members and friends. Receipt of inheritances is fairly criticized as not a truly exogenous event, yet one other type of windfall – winning the lottery – seems at first blush to be less vulnerable to this criticism of suspect endogeneity. Thus Lindh and Ohlsson (1996) estimated that the probability of self employment in Sweden would increase by 54 percent among those receiving lottery winnings. A lottery winning resulting in transition to a state of being wealthy would, of course, alleviate borrowing constraints. However, this finding may simply reflect lower risk-aversion among entrepreneurs rather than binding capital constraints. Quite irrespective of borrowing constraints, present interpretations of wealth's relationship to entry into entrepreneurship are all over the map (Parker, 2009, Chap. 9).

In an effort to overcome causality problems, some studies use unanticipated house price shocks as instrumental variables (IV) for wealth. Yet the muddy picture of conflicting results remains (Hurst and Lusardi, 2004; Disney and Hathergood, 2009). In this regard, the distinction between entries into low- and high-barrier industries may clarify causal relationships, because entry into capital-intensive industries may often be feasible only for individuals with either abundant personal wealth or such impressive human-capital traits that credit access is facilitated (Parker and van Praag, 2006). Bates (1990) has demonstrated that advanced educational credentials, in addition to personal assets, facilitate access to bank loans for small-business start-up capital. In low-barrier industries, conversely, little financial capital is typically needed. It is interesting in this respect to observe that many entrants to entrepreneurship possess little if any financial capital. A related point is made by Paul Geroski, who famously declared that `entry appears to be relatively easy, but survival is not' (Geroski, 1995, p. 23).

In general, sunk cost considerations may influence entrepreneurial entry decisions in capital-intensive industries. As Dixit (1989) noted, risk together with sunk costs can give agents an option value of waiting before switching occupations. This can encourage gradual entry, i.e., preliminary operations abbreviated in scope, as entrepreneurs "test the waters" before incurring the risks of quitting salaried employment and jeopardising their personal assets by entering entrepreneurship (Caves, 1998). Risk generates option values of remaining in one's present occupation while dabbling in entrepreneurship and deferring a costly switch. Only as the option value of waiting becomes sufficiently small, and/or returns in entrepreneurship become sufficiently high – or sunk cost barriers become sufficiently modest – does entry become worthwhile (Dixit and Rob, 1994).

Socio-demographic variables – gender, marital status, number of children, etc – also help to explain the identities of entrants to entrepreneurship (Parker, 2009). It is commonly observed that married men are particularly likely to become self-employed, perhaps because they have greater opportunities to specialise in high-potential enterprises while relying on their wives to specialise in household production (Hundley, 2000, 2001). Other researchers have highlighted how entrepreneurship entry rates vary, sometimes dramatically, between racially-defined groups, with African-Americans being significantly less likely to become entrepreneurs than white Americans. Asian-Americans, furthermore, tend to enter into entrepreneurship at higher rates than other minority groups. Reasons for these entry-rate differences appear to be rooted in the more abundant stocks of human and financial capital possessed by Asian-Americans, compared with other groups (Fairlie and Robb, 2008). While we expect these endowment differences to create differences in racial entry rates, it does not necessarily follow that entrant race will shape entry into low- rather than high-barrier industries once human-capital and financial-capital endowments of potential entrepreneurs are taken into account.

Other researchers have observed that immigrants are particularly prone to become entrepreneurs (Lofstrom, 2002; Schuetze and Antecol, 2006). Immigrants may be more likely to choose high- rather than low- barrier industries if the international transferability of their human capital is imperfect, e.g., if employers are uncertain about how to interpret foreign acquired education. On the other hand, factors making immigrants more likely to choose low-barrier industries include limited financial resources and blocked mobility considerations rooted in poor language skills.

Finally, labour market factors also affect entry into entrepreneurship. For example, a disproportionate number of entrants emanate from the ranks of the unemployed and from outside the labour force (Evans and Leighton, 1989), though not from the ranks of welfare recipients, who tend to be economically “marginal” (Dennis, 1998). Furthermore, long job tenure in paid employment is indicative of high-quality job-market matches between workers and employers, implying higher opportunity costs of entry and hence lower probabilities of transitions into entrepreneurship, all else equal. Again, little is known about how these influences differ, if at all, among entrants to low- and high-barrier industries.

3. Data and Descriptive Statistics

Data limitations, interacting with diverse definitions of what constitutes entrepreneurial activity, shape empirical findings on key determinants of entrepreneurship dynamics, including self-employment/business ownership entry. Household survey data, for example, may skew the identified entrepreneurial subset toward very small, often "casual" ventures, defined as business activities involving little or no input of labour time by the identified entrepreneur. The same applies to entrepreneurship data built upon government administrative and tax records. In the US, the Census Bureau's ambitious Characteristics of Business Owners (CBO) database, for example, is based upon samples drawn from federal income-tax returns filed by sole proprietorships, partnerships, and subchapter S corporations, many of which report trivial gross sales revenues (Bates, 1997). Other studies of entrepreneurial entry rely on databases, such as the Panel Study of Income Dynamics (PSID) data, which contain only small samples of entrepreneurs (Hurst and Lusardi, 2004; Bradford, 2003).

Seeking to avoid constraints imposed by small sample sizes and casual business presence, this study utilizes screened data drawn from the 1996 and 2001 panels of the US Census Bureau's Survey of Income and Program Participation (SIPP). Entrepreneurship will be operationalized as self-employment (Parker, 2009). Our sample includes adults aged between 25 and 59, irrespective of gender and labour force status. The age restriction is imposed to minimise confounding issues relating to schooling and retirement decisions. We also restrict our sample to individuals for whom wealth information is available; who are observed in the SIPP at least twice in consecutive years; and whose original state was not self-employment. These restrictions are necessary because our analysis of transitions into self-employment will be based on changes in year-over-year labour market states.

Each SIPP respondent is asked about his/her labor force status in the current month: recorded states included full-time and part-time paid-employment, full-time and part-time self-employment, unemployment, welfare recipient status, and `not in the labour force'. Full-time workers are defined as working at least 15 hours per week; part-timers work less than 15 hours per week. Individuals defined as unemployed experienced at least one week of unemployment during the survey month and did not satisfy the criteria for being classified as self employed or paid employed. Those defined as "welfare recipient" received Supplemental Security Income (SSI), Aid to Families with Dependent Children (AFDC)/Temporary Assistance for Needy Families (TANF) payments, or food stamps – and did not satisfy the definition criteria for self-employment, paid-employment or unemployment.

An individual is defined as self-employed if he or she reported both owning a business in the sample month and working at least 15 hours of work per week in that business. We initially impose the 15 hour per week requirement to identify self-employment entrants, and then explore the implications of altering the definition of entry by applying higher and lower hours-of-work standards to test the robustness of our findings.

The SIPP panels track respondents for several years, surveying them at four-month intervals. For this reason, the number of observations tracked in our probit models exceeds the number of unique individuals being analyzed. Our analysis of entry utilizes one observation per year for each individual, principally because wealth data are collected once per year. All wealth information utilized in our analysis relates to the previous year. Our focus is upon determinants of transitions from any labor force status into self employment; (lagged) original labor force status is controlled for in the probit estimations.

High- and Low-Barrier Industries

SIPP records industry subgroups for each individual engaged in work. To guide us in classifying an industry as low or high barrier, we use the 1997 Annual Capital Expenditure Survey (ACES) to determine average fixed private capital by industry, as well as the 2000 Census Bureau's five percent Public Use Microdata Sample (PUMS) to determine entrepreneurs' average educational attainment by industry. We classify as a low-barrier industry one which is intensive in neither human nor financial capital, compared with cross-industry averages of these inputs (see Lofstrom and Wang, 2009 for details). An industry intensive in either human or financial capital is classified as a high-barrier industry; specifically, average owner financial investment in high-barrier industries is in the top one-third, relative to all industry groups, and/or owner average years of formal education is in the top one-third. Industries classified as high (low) barrier often meet applicable cut-off values for both the owner financial-capital and human-capital traits. Applicable low-barrier industries include construction, transportation, retail, personal services, repair services, food services, and child-care services. High-barrier industries include business services, manufacturing, wholesale trade, professional services, entertainment services, and finance, insurance and real estate.[1]

Descriptive statistics

Table 1 presents the descriptive statistics for the SIPP samples of entrants and non-entrants. Consistent with most previous studies (Parker, 2009, Chap. 2), only 1.8 percent of non-self-employed adults annually transition into self-employment, defined as working at least 15 hours a week in one's business venture. Glancing down the columns, entrants generally exhibit

[1] Robustness of high/low barrier classifications was explored in various ways, including using CBO data to classify industry subgroups. Retailing emerged as a borderline case from this exercise, but otherwise a similar classification was obtained.

higher levels of education and personal wealth than non-entrants. However, the standard errors reveal that the observed higher mean wealth among entrants is not statistically significantly greater than that of non-entrants at conventional significance levels (the p value is 0.11). Importantly, the data reveal substantial differences between low- and high-barrier entrants. Specifically, low-barrier entrants possess markedly lower human- and financial-capital endowments. Especially striking is the concentration of individuals with at most high school education in low-barrier self-employment, and the concentration of highly educated individuals in high-barrier self-employment (all low-versus high-barrier differences in educational attainment levels shown in Table 1 are significantly different at the 1% significance level). Importantly, all group mean differences in household wealth between non-entrants, low-barrier entrants and high-barrier entrants are significant at the 5% level; furthermore, high-barrier industry entrants are significantly older, have fewer children, and are more likely to be white. Hispanics and immigrants are disproportionately found among low-barrier entrants. Entrants into low-barrier self-employment often come from non-work positions, although they are not significantly more likely to come from unemployment.

Table 2 explores further the detailed personal net-worth distributions characterizing non-entrants and the two entrant subgroups. Low-barrier industry entrants exhibit the lowest wealth holdings: they consistently have significantly lower wealth levels than non-entrants. High-barrier entrants are at the other end of the wealth spectrum; at none of the quintile cut-offs do we observe the lower end of the 95% percent confidence interval intersecting with the upper end of the non-entrant or low-barrier entrant wealth holding intervals.

[INSERT TABLES 1 AND 2 AROUND HERE]

4. Empirical Strategy

We initially estimate a "conventional" aggregate (pooled) probit model of entrepreneurship entry, treating all potential entrants as though the endowments facilitating successful entry are identical in all industry sectors:

$$E_{it} = \beta_0 + \beta_1 HC_{it} + \beta_2 FC_{it} + \beta_3 X_{it} + u_{it}$$

where E is entry, *HC* is human capital (measured using dummies for education higher than the base category of `high school dropout'), *FC* is personal wealth, X are the control variables, and *u* is a disturbance term. Simple binary probit is used to estimate this equation. Prior research suggests that β_2 (and perhaps β_1) will be positive and significant for entry. We first estimate this equation to show that our SIPP samples generate findings consistent with the prior research explaining entry into small-firm ownership. An alternative method of analysing entry might specify a probit model of entry conditioned on a set of covariates including intercept and slope industry dummies. Yet, since industry choice is jointly determined with the entry decision itself, these dummy variables would be endogenous. We next analyse entry in complementary ways, partly to deal with the endogeneity problem. First, we estimate a multinomial probit (MP) model with three outcomes: 1) self-employment entry into a low-barrier industry, 2) entry into a high-barrier industry in self-employment, and 3) remaining in the current labour market state (treated as the base category).

Like the better-known multinomial logit model, the MP model allows individual-specific covariates to affect each outcome in an outcome-specific way; unlike that model, however, MP is less restrictive by relaxing the assumption of the Independence of Irrelevant Alternatives (IIA). We believe the IIA assumption is not innocuous in the present context because the choice between becoming an entrepreneur in a high-barrier industry relative to remaining in the current labour market state is unlikely to be independent of the option of entry into a low-barrier industry (especially among less well educated or poorer people).

Our next approach models entrepreneurial entry jointly with industry type in a sample-selection model. A probit equation is proposed for both of the following choices: entry into any kind of full-time self-employment rather than remaining in the current job, and entry into a high-barrier rather than a low-barrier industry conditional on entry at all. Since industry choice is observed only for the selected sample of entrants, we have a Bivariate Sample Selection (BSS) model. Correlated unobserved factors which affect both choices are captured through an error covariance matrix which is estimated simultaneously with the other coefficients of the model. We do not hold strong priors about the sign of the correlation coefficient between unobservables, though if preferences for entrepreneurship are not positively correlated with the resources to fund it, a negative correlation between unobservables affecting entry and high-barrier entrepreneurship would be expected.

Our final empirical strategy involves an instrumental variable (IV) approach in which we use exogenous changes in local housing prices as an instrument for household wealth. Regional housing price variation has previously been used to instrument for access to financial capital in models of self-employment entry (e.g. Hurst and Lusardi, 2004; Disney and Hathergood, 2009). The intuition behind the validity of this approach is that fluctuations in the local housing market is correlated with the ability of would-be entrepreneurs to secure start-up capital through the mortgage market (e.g. an increase in local home values increases home equity available as collateral). Also, it is a plausible instrument as, holding other factors constant, it should not enter an individual's utility function directly (and comparing utility associated with the choice set is the assumed underlying framework for self-employment entry).

Specifically, we use median housing prices measured at the Metropolitan Statistical Area (MSA) level for MSA residents and state level for non-MSA residents. To obtain a time series of local level housing prices we start by using the 2008 American Community Survey (ACS) to estimate the median housing values by MSA and state level for non-MSA resident. We then used the Federal Housing Finance Agency's Housing Price Index (HPI) to back track what the local level housing values were in the relevant years for our study and data (i.e. 1996 to 2003). The median housing value is strongly correlated with our net worth measure. This is evident in our estimates from an OLS model of household net worth. The highly significant estimated median house price coefficient of 0.82 (t-value of 14.4) suggests that an increase in the median housing price is associated with an increase in household wealth by 82 percent. This is roughly in line with, but somewhat lower than, Hurst and Lusardi's (2004) estimated coefficient of 0.94 in a similar regression.

Beyond the validity of the instrument there are two potential limitations to an IV strategy in our empirical setting. First, since IV approaches are not suitable to specifications with endogenous dummy variables we are limited to models where wealth is measured continuously (e.g. as a quadratic function). Second, due to the additional necessary requirements to estimate the two parameter vectors in the multinomial setting with three choices, we rely on instrumental variable binomial probit (IVBP) specifications to assess the role of financial capital in self-employment entry.

We believe it is advantageous to estimate all of the MP, the BSS and the IVBP models. Estimating alternative models provides a robustness check on the results, since each individual model might be sensitive to underlying specification assumptions particular to those models.

5. Results

The Pooled Probit Model

Table 3 presents the marginal effects of the "conventional" pooled, or aggregated, probit model which does not distinguish entry by industry type. Two specifications are estimated: first, wealth enters as continuous variables (wealth and wealth squared); second, it is represented by a quintile breakdown. In both specifications, higher levels of education are significantly positively related to entry into self-employment, especially at higher levels. The effect of wealth (column 1) upon entry is small and positive but exhibits a decreasing rate; when wealth is measured in quintiles (column 2), its significance emerges only in the top quintile, which is consistent with the wealth/entry relationship reported by Hurst and Lusardi (2004). These findings replicate the common conclusions that entrants into entrepreneurship are more highly educated and wealthier than non-entrants.

[INSERT TABLES 3 & 4 ABOUT HERE]

The Multinomial Probit (MP) Model

Table 4 presents the results of estimating the MP model. The three outcomes are: remaining in the current labour market state (the omitted category), entry into a low-barrier industry, and entry into a high-barrier industry. Marginal effects are reported in all cases: these are interpreted relative to the omitted category. The first column of the table conditions only on schooling dummies, while the second column conditions only on household net worth, using quintile dummy wealth measures. The third column includes both schooling and wealth variables, as well as a full set of control variables.

Consistent with Table 1 summary statistics, entrants to high-barrier industries are significantly more likely to be well educated, relative to non-entrants (see the first column of Table 4). The effects of education on selection into low-barrier industries, however, differ profoundly, suggesting that people educated to college level and higher avoid entry into low-barrier industries. Thus advanced education positively predicts entry into some lines of small business, while negatively predicting entry into others. These findings remain robust to including financial capital and control variables in column 3, although the absolute sizes of the coefficients decline somewhat, compared to those reported in column 1. Column 2 of Table 4 analyses the effects of including household net worth by quintile (the base category is wealth in the lowest quintile). There is no tendency toward entrepreneurial entry into either high- or low-barrier fields among those in the lower quintiles of the wealth distribution. Those in the top two wealth quintiles are actually less likely to enter a low-barrier industry, relative to the bottom-quintile individuals; the opposite pattern describes entry into high-barrier industries. Regarding wealth's impacts upon low-barrier industry entry, these results weaken in column 3, when additional covariates are included in the specification, but it remains the case that those most likely to enter entrepreneurship via high-barrier industries are those in the top two quintiles of the wealth distribution.

The control variables in column 3 also highlight interesting commonalities and differences in the nature of entry by industry type. Consistent with previous findings, women are significantly less likely than men to enter any type of self-employment, as are the youngest and oldest individuals. Immigrants are significantly more likely to make a transition into self-employment than native-born Americans, especially in low-barrier industries. African-Americans are significantly less likely to enter low-barrier (but not high-barrier) self-employment than to remain in their current labour market position, while Asian-Americans are significantly less likely to enter high-barrier (but not low-barrier) self-employment. The richness of the racial composition of entry is lost in the pooled probit, where the results blandly state that non-whites are simply less likely to enter self-employment.

Also consistent with previous findings (e.g. Storey, 1991), the unemployed and those not in the labour force are also proportionately more likely to transition to self-employment than full-time employees are (the base category). Further, welfare recipients are significantly *less* likely to make a transition (Dennis, 1998). Finally, we observe a U-shaped relationship between years at the job and the probability of making a switch into self-employment (c.f. Parker, 2009, Chap. 4). These labour market determinants of entrepreneurial transitions predict entry into both high- and low-barrier industries in a broadly similar manner.

The Option Value of Starting Out Small

Regarding the risk of starting a new venture, Caves (1998) observed that considerable uncertainty in outcomes often causes start-ups to begin small, even in industries where scale economies prevail: "small-scale entry commonly provides a real option to invest heavily if early returns are promising" (p.1976). By defining entrants as those working at least 15 hours a week in their new venture, are we capturing those entrants who have chosen to test the waters, to dabble in entrepreneurship before making a costly switch to self employment? Since we really do not know, our next probit exercise entails relaxing the hours worked cut-off and identifying as entrants into self-employment all those who report new ownership of a business and work hours greater than zero in the new venture during the survey month. The additional entrants – those working less than 15 hours in their new venture – were not counted as entrants in our Table 4 MP model, and they differ from the entrants identified in Table 1 in several interesting ways (see Appendix Table A1 for details). In brief, they are a wealthier and more highly educated group, primarily consisting of full-time employees. These traits indicate those initially choosing to work less than 15 hours in their new venture include workers who face high opportunity costs if they choose to leave paid employment for entrepreneurship. To test the robustness of our Table 4 findings predicting entry, we re-estimated the full MP model (including education, wealth, and control variables) to include as entrants *all* new business owners who worked more than zero hours in their new venture (the observed low-barrier and high-barrier entry rates without the 15 hours requirement are 0.0148 and 0.0137 respectively). Results of this exercise appear in Table 5, column 1.

Using our expanded definition of entrants, we observe a *stronger* positive impact of advanced education on the likelihood of entry in high-barrier fields and a stronger negative impact on low-barrier entry. Regarding household wealth, a stronger likelihood of entry into high-barrier industries is now apparent, and the top three wealth quintiles are now positive, statistically significant predictors of entry (Table 5, column 1). Wealth levels continue to be unrelated to entry in the low-barrier fields. The overall goodness of fit of the MP model improves markedly when the entrant definition is expanded to include all new business owners, in comparison with Table 4's outcome. The control variables generally perform consistently in the two MP models, with one noteworthy exception. Among prospective entrepreneurs facing low opportunity costs of entry – particularly the unemployed and those not in the labor force – applying an over 15-hour work constraint to define entry (Table 4) generated a finding that the low-opportunity-cost groups were more likely than others to enter. Relaxing this constraint, the opposite relationship between entry and non-work status emerges: relative to those coming from an active work status, the non-worker subgroups are now *less* likely to enter into ownership of a new venture (Table 5, column 1).

[INSERT TABLE 5 ABOUT HERE]

Those testing the waters, working only a few hours in their new ventures, seem to be collectively behaving as if their decision to pursue entrepreneurship is shaped by opportunity-cost considerations. This relatively highly educated, high income, largely employed group appears to be approaching entrepreneurship gradually, consistent with the explanations of entry advanced by Dixit (1989), Dixit and Rob (1994), Caves (1998), and others. This observation raises an obvious further question: if these potential entrepreneurs facing high opportunity costs of entry really are testing the waters, do a significant number of them eventually take the plunge, committing additional hours of work to their new venture in subsequent time periods? The SIPP database is ideally designed to test whether the work hours of these part-time self-employed increases in future periods.

Defining the part-time self-employed as those working less than 15 hours in their new venture in the interview period, we proceed by utilizing part-timer status as an explanatory variable. We distinguish those entering into full-time self employment (those working 15 or more hours in their new firm) in a high- or low-barrier industry from non-entrants. We utilize the same explanatory variables in Table 5 column 1, plus the new part-timer variable, to predict entry into full-time self employment; results from this MP exercise are reported in Table 5, column 2. The new part-time self employment variable emerges as the single most powerful predictor of entry into full-time self employment. Clearly, the dynamics of entry, for many, entail pursuing self employment initially by working only a few hours per week in one's new venture. Assuming that this exploratory phase proceeds smoothly, entrants proceed by increasing their work hours in their young firms.

When entry is defined as working 30 or more hours a week in one's new venture and the Table 5 MP model is re-estimated – including the part-time self employment explanatory variable – this pattern emerges once again as the dominant predictor of full-time entry (model not reported). It is noteworthy that being a part-timer strongly predicts entry into both high-barrier and low-barrier industries. Among the part-time self employed, furthermore, it is the more highly educated who tend to move up to full-time status most cautiously, which is consistent with them facing higher opportunity costs of entry than their less well educated counterparts. One limitation of using part-time self employment to predict entry, of course, is the fact that it is likely to be endogenous. Yet, for a variety of different MP specifications, we find consistently that the people who are most likely to transition into full-time self-employment are those who are already self-employed on a part-time basis.

Our findings regarding entry into self employment in high- and low-barrier industries have implications applicable to ongoing controversies regarding wealth endogeneity and entry decisions. Hurst and Lusardi's (2004) speculation that wealthy people may be particularly inclined to pursue self employment is one possible interpretation of the relationship between personal net worth to entry, but it does not fit the facts terribly well. In particular, it fails to explain why wealth is unrelated to entrepreneurial entry in low-barrier industries, which account for most new firm formations observed in this study (the low-barrier and high-barrier entry rates are 0.99 percent and 0.84 percent respectively using the at least 15 hours restriction). Some wealthy entrants undoubtedly view entrepreneurship as a lifestyle choice – something of a "superior good" as Hurst and Lusardi have suggested (2004) –yet why would this preference apply solely to new ventures formed in high-barrier industries? Furthermore, those entering into self employment most gradually – initially working 15 or fewer hours per week in their new venture – are not only the more highly educated and highest income earners; they are also wealthier, on average, than entrants initially working longer hours in their new enterprise – $28,000 wealthier, on average. The wealthier part-time entrants described above are behaving as though they are highly sensitive to the opportunity costs of entry, which encourages them to test the waters before committing seriously to self employment.

The Bivariate Sample Selection (BSS) Model

Table 6 presents estimates of the BSS model. Two specifications are reported. The first exactly identifies the model by excluding the "years at job" variable from the high-barrier probit equation; the other over-identifies it by imposing an additional exclusion restriction ("annual earnings in the previous year") on the high-barrier equation. The rationale for these restrictions is that one might expect the length of a previous job match and earnings received there to significantly affect their willingness to quit and enter entrepreneurship, without necessarily predisposing a person who actually does enter to do so via a particular type of industry. The final entry at the foot of the table presents a Likelihood Ratio (LR) test which supports the validity of the exclusion restrictions. Table 6 also presents estimates of the correlation coefficient between the error terms of the two probit equations: it is significantly different from zero in the over-identified specification. Its negative sign suggests that people with unobserved characteristics making them more likely to want to become entrepreneurs are more likely to enter a low-barrier industry. As noted earlier, this is precisely what one would expect if tastes for entry and resources required for entry are not positively correlated.

[INSERT TABLE 6 AROUND HERE]

Overall, the coefficients in the main body of Table 6 are similar in both the exactly- and over-identified specifications. They largely bear out the results obtained from the MP analysis. In particular, educated people are significantly more likely to enter full-time self-employment in high- rather than in low-barrier industries. Also as before, entry into self-employment is associated with wealth only at higher wealth levels, and in high- rather than in low-barrier industries. The control variables also have broadly similar effects in Table 6 to those observed in Table 4 (note that the coefficients in the 'High Barrier' columns record whether their effects are significantly different in terms of the nature of the industry). However, some significant differences are observed in the final column of Table 6 for age, gender and marital status – these differences were not obvious from Table 4. Furthermore, Table 6 clearly shows that immigrants, the unemployed, those not in the labour force, and part-time workers are significantly more likely to enter low- relative to high-barrier industries. This seems plausible, since these workers are less likely to possess the resources needed to enter and succeed in self-employment in high-barrier industries.

The Instrumental Variable Binomial Probit (IVBP) Model

Finally, we turn to the results of our last strategy: using exogenous changes in median local housing prices as an instrument for household net worth. The objective here is to determine if our key finding that wealth (and education) matters differently in different industries classified by entry barriers holds when the potential endogeneity of wealth is addressed. To do so we estimate separate Instrumental Variable binary probit models of entry into any type of self-employment (i.e. no industry barrier distinction) as well as specifically entry into low-barrier and high-barrier industries. The low-barrier entry models are estimated based on a sample excluding those who we observe entering into high-barrier self-employment while the high-barrier entry models exclude observed low-barrier entrants.

For our interpretation of wealth effects to hold up, we would expect that the IVBP estimates would reveal a stronger wealth-entry relationship in the high-barrier self-employment entry case than in the any-entry case. We would also expect to see no relationship between wealth and low-barrier industry entry. The results in Table 7 provide evidence supporting this.

[INSERT TABLE 7 AROUND HERE]

The estimates in the first three columns are obtained relying on lagged household net worth without using any instrument. They show that the significant relationship between wealth and self-employment entry without any industry barrier distinction observed in Table 3 (repeated in the first column in Table 7) is driven by high-barrier entries. It is insignificant in the low-barrier entry models.

The IVBP results reported in the last three columns of Table 7 also provide evidence of a relationship between wealth and entry but only with respect to high-barrier industries. As with Hurst and Lusardi (2004), our estimates fail to reveal any support for binding capital constraints with respect to overall self-employment entry. Our low-barrier entry results, not surprisingly, also point to a lack of predictive power between wealth and entry. However, the high-barrier IV wealth estimates suggest a positive and statistically significant relationship between household wealth and entry.[2] Taken at face value, the point estimates suggest a more widespread presence of capital constraints among entrepreneurs seeking entry into high-barrier industries than the non-IV results. However, the relative lack of precision of the IV estimates cautions against

[2] The Wald tests of exogeneity presented at the bottom of the table indicate that there is no wealth endogeneity in the overall self-employment entry and low-barrier models (and hence that the IVBP estimator is not efficient). The test statistic for high-barrier entry, the last column, however rejects the null hypothesis of no endogeneity and hence suggests that the IVBP model is preferred.

attaching too much weight to the functional form of the relationship. Instead, a more valuable insight from the IVBP strategy is that these results provide evidence consistent with all of our other empirical findings with respect to wealth (and education).

6. Conclusions

This study has shown that key entrepreneurial entry determinants are dissimilar in high-barrier industries versus low-barrier fields. Characteristics of potential entrepreneurs draw them toward some types of new ventures and away from others. Educational levels, in particular, predict self-employment entry, but not exactly in the manner that conventional wisdom leads us to expect. The college-education level variable coefficients stand out as strongly positive for high-barrier fields, yet the exact opposite outcome describes low-barrier industry entry. College graduates positively select into industries like professional services where expected earnings are high, while steering clear of low-remuneration fields like personal and repair services. Wealth holdings positively predict entry into high-barrier industries but do not significantly impact the likelihood of entry into low-barrier fields. We find that the top two quintiles of the personal wealth distribution consistently predict entry into high-barrier industries; using a more expansive definition of entry, the top three wealth quintiles positively predict self-employment entry. Thus, across a wide range of the distribution, wealth appears to alleviate capital constraints, facilitating entrepreneurial entry in high-barrier industries.

In contrast, it appears that conventional pooled probit entry results are driven by the factors explaining entry into high-barrier fields, and so provide misleading indications of the relationships between human and financial capital and self-employment entries into low-barrier industries – which is where most transitions take place. This finding accentuates the importance for understanding determinants of entrepreneurial entry of disaggregating entries by industry.

Our findings carry several policy implications. First, if policy-makers wish to promote entry into high-barrier industries, they should tackle constraints associated with low levels of human and financial capital. Policy-makers might also encourage workers to enter part-time self-employment prior to plunging head on into full-time operation of a new business venture. The part-time self-employed are, after all, the group most likely to transition into full-time self-employment later on. By entering gradually into ownership of a firm, workers preserve the possibility of retaining paid employment, thus maintaining a fall-back in case the new venture proves to be nonviable. Future research should evaluate the relative success of the gradual start-up strategy.

The human- and financial-capital constraints widely cited as determinants of entry patterns, in summary, operate quite differently in the various business segments. Yet self-employment entry has commonly been examined empirically in one-size-fits-all econometric models, an approach which fails to capture key entry dynamics. This is because industry context heavily shapes the impacts of owner resource endowments on firm entry. Limitations of one-size-fits-all models are rooted in the fact that major differences in entry barriers typify different industry subgroups. We believe that further insights and policy implications will emerge as researchers increasingly recognise the importance of this distinction and as this research agenda is advanced using richer longitudinal datasets.

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Table 1. Summary Statistics, Sample Means and Standard Errors, Self-Employment Entry Sample

	No Entry		Entry					
			All		Low Barrier		High Barrier	
Observed Probability	0.982		0.018		0.010		0.008	
	Mean	S.E	Mean	S.E	Mean	S.E	Mean	S.E
Years of Schooling	13.26	(0.0082)	13.84	(0.0582)	12.78	(0.0689)	15.11	(0.0825)
High School Dropout	0.111	(0.0009)	0.082	(0.0056)	0.129	(0.0093)	0.026	(0.0047)
High School Graduate	0.310	(0.0013)	0.263	(0.0092)	0.360	(0.0136)	0.149	(0.0109)
Some College	0.306	(0.0013)	0.307	(0.0095)	0.336	(0.0132)	0.273	(0.0136)
College Graduate	0.186	(0.0011)	0.215	(0.0085)	0.132	(0.0094)	0.314	(0.0142)
Post College	0.087	(0.0008)	0.132	(0.0068)	0.044	(0.0056)	0.238	(0.0126)
Age	41.1	(0.0272)	41.2	(0.1872)	40.5	(0.2492)	42.0	(0.2810)
Female	0.533	(0.0014)	0.411	(0.0100)	0.415	(0.0137)	0.407	(0.0148)
Married	0.640	(0.0014)	0.674	(0.0098)	0.682	(0.0134)	0.664	(0.0145)
Number of Children	0.960	(0.0033)	1.004	(0.0255)	1.096	(0.0360)	0.895	(0.0356)
Child 5 or younger	0.261	(0.0012)	0.274	(0.0092)	0.299	(0.0128)	0.245	(0.0131)
Non-Hispanic White	0.717	(0.0013)	0.757	(0.0091)	0.708	(0.0131)	0.816	(0.0122)
Hispanic	0.117	(0.0010)	0.115	(0.0069)	0.155	(0.0106)	0.066	(0.0081)
African American	0.119	(0.0009)	0.086	(0.0061)	0.091	(0.0086)	0.081	(0.0085)
Asian	0.027	(0.0005)	0.024	(0.0031)	0.027	(0.0044)	0.020	(0.0043)
Other Ethnicity	0.020	(0.0004)	0.018	(0.0027)	0.020	(0.0037)	0.017	(0.0039)
Immigrant	0.174	(0.0011)	0.199	(0.0083)	0.230	(0.0119)	0.163	(0.0112)
Lagged Variables								
Part-Time Self-Employed	0.016	(0.0004)	0.245	(0.0088)	0.201	(0.0112)	0.297	(0.0139)
Full-Time Wage/Salary	0.743	(0.0012)	0.485	(0.0103)	0.498	(0.0140)	0.469	(0.0151)
Part-Time Wage/Salary	0.013	(0.0003)	0.014	(0.0024)	0.016	(0.0035)	0.012	(0.0033)
Unemployed	0.033	(0.0005)	0.061	(0.0051)	0.067	(0.0074)	0.053	(0.0068)
Welfare	0.052	(0.0006)	0.017	(0.0025)	0.023	(0.0040)	0.009	(0.0028)
Not in the Labor Force	0.142	(0.0010)	0.178	(0.0079)	0.193	(0.0113)	0.159	(0.0110)
Years at Job	5.57	(0.0215)	2.44	(0.1026)	2.40	(0.1364)	2.48	(0.1554)
Household Net Worth	150,333	(4108)	255,499	(65364)	122,067	(8402)	413,830	(140001)
Number of Observations	142,040		2,667		1,447		1,200	
Number of Individuals	65,115		1,927		1,076		851	

Note: Standard errors in parentheses. Source: 1996 and 2001 SIPP.

Table 2. Lagged Household Net Worth Distribution, with 95% Confidence Intervals, by Self-Employment Entry.

	No Entry		Entry					
			All		Low Barrier		High Barrier	
Mean	150,333		255,499		122,067		413,830	
	142,282	158,384	127,329	383,669	105,586	138,549	139,428	688,232
Median	47,175		63,001		38,837		99,733	
	46,449	47,884	56,341	68,052	32,459	46,054	86,921	114,139
Quintile Cut-off								
20th Percentile	991		1,938		642		8,414	
	925	1,152	1,226	2,995	0	1,292	4,816	12,227
40th Percentile	23,902		32,469		15,892		62,968	
	23,411	24,432	25,912	37,859	12,164	20,425	54,374	69,095
60th Percentile	78,187		100,801		68,758		156,256	
	77,227	78,989	90,564	110,674	59,115	76,189	136,040	176,326
80th Percentile	193,821		266,399		180,747		382,123	
	192,034	196,380	243,771	288,844	166,729	203,250	332,593	422,748
Number of Obs.	142,040		2,647		1,447		1,200	
Number of Individuals	65,115		1,927		1,076		851	

Note: The two values directly underneath each summary statistic entry represent the 95 percent confidence interval. Source: 1996 and 2001 SIPP

Table 3. Probit Models of Self-Employment Entry, No Industry Barrier Distinction.

	Col. 1	**Col. 2**
High School Graduate	0.003	0.003
	(2.65)	(2.55)
Some College	0.005	0.005
	(3.64)	(3.45)
College Graduate	0.006	0.006
	(3.89)	(3.55)
Post College Degree	0.011	0.010
	(4.94)	(4.60)
Household Net Worth (in $100,000s)	0.0002	
	(3.29)	
Household Net Worth^2	-0.00001	
	(2.36)	
Household Net Worth in 2nd Quintile		0.001
		(0.86)
Household Net Worth in 3rd Quintile		-0.0001
		(0.15)
Household Net Worth in 4th Quintile		0.0001
		(0.10)
Household Net Worth in Top Quintile		0.004
		(3.15)
Age	0.002	0.002
	(5.15)	(5.20)
Age^2/100	-0.002	-0.0019
	(5.00)	(5.12)
Female	-0.009	-0.009
	(14.06)	(14.10)
Married	0.0007	0.001
	(0.93)	(0.83)
Number of Children	0.0003	0.000
	(0.82)	(0.76)
Child 5 or younger	-0.00003	0.000
	(0.03)	0.00
Hispanic	-0.0003	0.000
	(0.31)	(0.17)
African American	-0.0023	-0.002
	(2.43)	(2.09)
Asian	-0.004	-0.0042
	(2.90)	(2.91)
Other Ethnicity	-0.003	-0.0031
	(1.86)	(1.80)
Immigrant	0.005	0.00459

	(4.42)	(4.40)
Part-Time Self-Employment	0.153	0.1526
	(18.70)	(18.60)
Part-Time Wage/Salary	0.004	0.004
	(1.42)	(1.35)
Unemployed	0.012	0.012
	(4.99)	(4.98)
Welfare	-0.008	-0.008
	(7.93)	(7.81)
Not in the Labor Force	0.006	0.006
	(4.72)	(4.66)
Years at Job	-0.001	-0.001
	(9.87)	(9.89)
Years at Job^2/100	0.003	0.003
	(5.76)	(5.73)
Number of Observations	144,687	
Log Likelihood	-11,659	-11,654

Note: Z-statistics in parentheses. Source: 1996 and 2001 SIPP

Table 4. Multinomial Probit Models of No Entry, Low Barrier Entry or High Barrier Entry: Marginal Effects

Variable	Column 1		Column 2		Column 3	
	Entry to Low Barrier	Entry to High Barrier	Entry to Low Barrier	Entry to High Barrier	Entry to Low Barrier	Entry to High Barrier
High School Graduate	-0.0001	0.004			0.001	0.004
	(0.15)	(2.98)			(1.43)	(3.02)
Some College	-0.001	0.008			0.0003	0.007
	(1.74)	(5.13)			(0.39)	(5.04)
College Graduate	-0.004	0.017			-0.002	0.015
	(5.92)	(6.31)			(3.24)	(5.73)
Post College Degree	-0.005	0.030			-0.004	0.026
	(8.74)	(6.56)			(5.29)	(5.84)
Household Net Worth in 2nd Quintile			0.0004	0.0004	0.0001	0.001
			(0.59)	(0.55)	(0.21)	(0.86)
Household Net Worth in 3rd Quintile			-0.001	0.001	-0.0004	0.001
			(1.29)	(0.91)	(0.57)	(0.88)
Household Net Worth in 4th Quintile			-0.002	0.002	-0.001	0.001
			(2.82)	(2.83)	(1.03)	(2.00)
Household Net Worth in Top Quintile			-0.002	0.010	-0.0001	0.003
			(2.97)	(6.73)	(0.19)	(4.08)
Age					0.001	0.0004
					(5.22)	(2.61)
$Age^2/100$					-0.001	-0.0005
					(5.41)	(2.41)
Female					-0.005	-0.003
					(9.86)	(9.32)
Married					0.001	-0.0004
					(1.96)	(1.08)
Number of Children					0.0001	0.0000
					(0.50)	(0.08)
Child 5 or younger					0.0004	-0.0003
					(0.65)	(0.67)
Hispanic					0.000	-0.0005
					(0.36)	(0.78)
African American					-0.002	-0.0005
					(2.67)	(0.89)
Asian					-0.001	-0.002
					(0.78)	(3.63)
Other Ethnicity					-0.001	-0.002
					(1.35)	(1.80)
Immigrant					0.002	0.001
					(3.27)	(2.48)
Part-Time Wage/Salary					0.003	0.0003
					(1.49)	(0.23)
Unemployed					0.006	0.004
					(3.77)	(3.29)

Welfare			-0.004	-0.002
			(5.71)	(4.10)
Not in the Labor Force			0.003	0.002
			(3.90)	(2.84)
Years at Job			-0.001	-0.001
			(7.02)	(7.19)
Years at Job^2/100			0.002	0.001
			(4.16)	(4.28)
Number of Observations		141,684		
Log Likelihood	-4,592,897	-46,514,630	-44,251,326	

Note: Z-statistics in parentheses. Source: 1996 and 2001 SIPP

Table 5. Multinomial Probit Models of No Entry, Low Barrier Entry or High Barrier Entry With No Hours Restrictions on the Definition of Entrants: Marginal Effects

	Column 1		Column 2	
Variable	**Entry to Low Barrier**	**Entry to High Barrier**	**Entry to Low Barrier**	**Entry to High Barrier**
High School Graduate	0.001	0.003	0.001	0.004
	(0.49)	(2.27)	(1.25)	(3.14)
Some College	0.001	0.009	0.000	0.007
	(1.09)	(5.96)	(0.03)	(5.22)
College Graduate	-0.004	0.021	-0.003	0.015
	(3.76)	(7.80)	(4.72)	(6.06)
Post College Degree	-0.006	0.037	-0.005	0.026
	(5.94)	(8.30)	(8.08)	(6.25)
Household Net Worth in 2nd Quintile	-0.001	0.001	0.000	0.001
	(0.96)	(1.18)	(0.17)	(1.09)
Household Net Worth in 3rd Quintile	0.000	0.002	-0.001	0.001
	(0.19)	(2.33)	(0.83)	(0.84)
Household Net Worth in 4th Quintile	0.000	0.003	-0.001	0.001
	(0.17)	(3.86)	(1.22)	(1.71)
Household Net Worth in Top Quintile	0.001	0.007	-0.000	0.003
	(0.97)	(6.68)	(0.03)	(4.21)
Age	0.002	0.001	0.001	0.001
	(6.33)	(5.76)	(4.77)	(2.66)
$Age^2/100$	-0.002	-0.001	-0.001	-0.001
	(5.87)	(4.96)	(4.84)	(2.45)
Female	-0.005	-0.004	-0.005	-0.003
	(7.67)	(8.42)	(10.33)	(9.46)
Married	0.002	-0.001	0.001	-0.001
	(2.50)	(1.45)	(2.19)	(1.28)
Number of Children	0.000	0.000	0.000	0.000
	(1.03)	(.016)	(0.70)	(0.06)
Child 5 or younger	0.002	0.001	0.000	-0.000
	(2.29)	(1.80)	(0.44)	(0.51)
Hispanic	0.000	-0.003	0.000	-0.001
	(0.20)	(3.71)	(0.37)	(1.17)
African American	-0.003	-0.002	-0.002	-0.000
	(3.70)	(3.11)	(2.28)	(0.43)
Asian	-0.003	-0.004	-0.001	-0.002
	(2.32)	(5.33)	(0.52)	(4.12)
Other Ethnicity	-0.002	-0.001	-0.001	-0.001
	(1.40)	(1.08)	(1.03)	(1.56)
Immigrant	0.001	0.000	0.003	0.002
	(1.51)	(0.02)	(3.50)	(2.63)
Part-Time Self-Employment			0.078	0.065
			(12.26)	(11.43)
Part-Time Wage/Salary	-0.004	-0.005	0.004	0.000
	(2.36)	(5.92)	(1.49)	(0.22)

Unemployed	-0.003	-0.003	0.006	0.004
	(2.57)	(4.67)	(3.68)	(3.27)
Welfare	-0.010	-0.008	-0.004	-0.003
	(20.10)	(20.11)	(6.31)	(4.48)
Not in the Labor Force	-0.006	-0.005	0.003	0.002
	(9.43)	(13.75)	(3.71)	(2.83)
Years at Job	-0.003	-0.003	-0.001	-0.001
	24.93)	(26.52)	(6.84)	(7.04)
Years at Job^2/100	0.008	0.007	0.002	0.001
	(19.15)	(21.53)	(3.85)	(4.18)
Number of Observations	145,338		144,687	
Log Likelihood	-78,553,780		-51,995,907	

Note: Z-statistics in parentheses. Source: 1996 and 2001 SIPP

Table 6. Bivariate Sample Selection Model. Probability of High-Barrier versus Low-Barrier Start-up, Adjusting for Selection on Entry into Self-Employment.

Variable	**One Exclusion Restriction** (Exact Identification)		**Two Exclusion Restrictions** (Over Identified)	
	Entry into Self-Employment	**High Barrier**	**Entry into Self-Employment**	**High Barrier**
High School Graduate	0.094	0.306	0.092	0.193
	(2.65)	(2.36)	(2.57)	(1.68)
Some College	0.131	0.666	0.123	0.462
	(3.66)	(4.70)	(3.44)	(3.09)
College Graduate	0.155	1.285	0.134	0.946
	(3.95)	(7.39)	(3.37)	(4.25)
Post College Degree	0.240	1.680	0.200	1.233
	(5.63)	(7.70)	(4.51)	(4.32)
Household Net Worth in 2nd Quintile	0.026	0.109	0.025	0.079
	(0.88)	(1.21)	(0.86)	(1.05)
Household Net Worth in 3rd Quintile	-0.005	0.110	-0.009	0.100
	(0.15)	(1.21)	(0.29)	(1.34)
Household Net Worth in 4th Quintile	0.003	0.225	-0.003	0.185
	(0.10)	(2.43)	(0.09)	(2.32)
Household Net Worth in Top Quintile	0.104	0.350	0.088	0.247
	(3.37)	(3.51)	(2.81)	(2.63)
Age	0.049	-0.042	0.046	-0.050
	(5.20)	(1.39)	(4.93)	(2.10)
$Age^2/100$	-0.057	0.051	-0.055	0.061
	(5.12)	(1.42)	(4.88)	(2.15)
Female	-0.272	0.022	-0.254	0.128
	(14.53)	(0.26)	(12.96)	(2.06)
Married	0.018	-0.117	0.015	-0.096
	(0.83)	(1.78)	(0.69)	(1.73)
Number of Children	0.008	-0.011	0.007	-0.013
	(0.76)	(0.40)	(0.67)	(0.55)
Child 5 or younger	0.000	-0.009	-0.002	-0.006
	0.00	(0.12)	(0.06)	(0.10)
Hispanic	-0.006	-0.132	-0.004	-0.100
	(0.17)	(1.25)	(0.11)	(1.15)
African American	-0.065	0.038	-0.063	0.061
	(1.97)	(0.37)	(1.90)	(0.75)
Asian	-0.148	-0.370	-0.147	-0.221
	(2.45)	(1.88)	(2.42)	(1.32)
Other Ethnicity	-0.105	0.050	-0.105	0.082
	(1.59)	(0.24)	(1.59)	(0.49)
Immigrant	0.127	-0.083	0.131	-0.121
	(4.80)	(0.99)	(4.94)	(1.88)
Part-Time Self-Employment	1.284	-0.111	1.292	-0.687
	(38.05)	(0.31)	(37.22)	(2.90)
Part-Time Wage/Salary	0.110	-0.311	0.136	-0.366
	(1.51)	(1.39)	(1.84)	(2.06)
Unemployed	0.272	-0.120	0.292	-0.285

	(6.40)	(0.77)	(6.68)	(2.48)
Welfare	-0.317	0.049	-0.289	0.120
	(5.48)	(0.21)	(4.87)	(0.67)
Not in the Labor Force	0.153	-0.107	0.184	-0.226
	(5.24)	(1.00)	(5.56)	(2.92)
Years at Job	-0.044		-0.044	
	(9.80)		(9.58)	
Years at Job^2/100	0.095		0.096	
	(5.76)		(5.88)	
Annual Earnings Previous Year			0.000001	
			(3.29)	
rho = Corr(u_1,u_2)	-0.249		-0.684	
Chi square, Wald test, H_0: rho=0	0.75		2.74	
Log Likelihood	-13,216.66		-13,211.79	
LR Test (Exact v. Over)		9.74		
Number of Observations		144,687		

Note: Z-statistics in parentheses. Parameters are the estimated coefficients and not marginal effects.
Source: 1996 and 2001 SIPP

Table 7. Instrumental Variable Probit Models of Self-Employment Entry with Industry Barrier Distinction

	Entry - No Instruments			Entry - Instruments		
	Any	Low-Barrier	High-Barrier	Any	Low-Barrier	High-Barrier
Household Net Worth ($100,000s)	0.00017	-0.00006	0.00010	0.0010	-0.0011	0.0022
	(3.29)	(0.78)	(4.83)	(0.79)	(1.23)	(2.03)
Household Net Worth^2	-0.000012	0.000002	-0.000008	0.00033	-0.00006	0.00036
	(2.36)	(0.67)	(3.67)	(0.72)	(0.18)	(0.88)
High School Graduate	0.003	0.001	0.004	0.003	0.002	0.002
	(2.65)	(1.34)	(3.26)	(2.43)	(1.52)	(1.87)
Some College	0.005	0.0001	0.008	0.004	0.001	0.004
	(3.64)	(0.17)	(5.36)	(2.92)	(0.64)	(3.52)
College Graduate	0.006	-0.003	0.017	0.004	-0.003	0.006
	(3.89)	(4.40)	(6.23)	(1.83)	(1.67)	(3.67)
Post College Degree	0.011	-0.004	0.029	0.004	-0.003	0.007
	(4.94)	(7.29)	(6.37)	(0.73)	(0.83)	(1.79)
Age	0.002	0.001	0.0005	0.002	0.001	0.001
	(5.15)	(4.65)	(2.77)	(3.93)	(2.39)	(2.63)
Age^2/100	-0.002	-0.001	-0.0005	-0.003	-0.001	-0.002
	(5.00)	(4.72)	(2.41)	(3.75)	(2.12)	(2.65)
Female	-0.009	-0.005	-0.003	-0.011	-0.006	-0.005
	(14.06)	(10.18)	(9.41)	(10.33)	(9.08)	(5.32)
Married	0.001	0.001	-0.0004	-0.001	0.002	-0.003
	(0.93)	(2.16)	(0.96)	(0.75)	(2.13)	(3.37)
Number of Children	0.0003	0.0002	0.00002	0.0001	0.0003	-0.0002
	(0.82)	(0.72)	(0.12)	(0.17)	(0.81)	(0.45)
Child 5 or younger	-0.00003	0.0003	-0.0003	0.001	0.000	0.001
	(0.03)	(0.45)	(0.62)	(0.74)	(0.18)	(1.19)
Hispanic	-0.0003	0.0003	-0.0009	0.001	0.00001	0.001
	(0.31)	(0.33)	(1.42)	(0.65)	(0.01)	(0.76)
African American	-0.002	-0.002	-0.001	-0.001	-0.002	0.002
	(2.43)	(2.28)	(0.95)	(0.59)	(2.43)	(1.82)
Asian	-0.004	-0.001	-0.002	-0.002	-0.002	-0.0003
	(2.90)	(0.56)	(3.94)	(0.42)	(0.55)	(0.08)
Other Ethnicity	-0.003	-0.001	-0.002	-0.002	-0.003	0.001
	(1.86)	(0.99)	(1.73)	(0.53)	(1.12)	(0.46)
Immigrant	0.005	0.003	0.002	0.002	0.004	-0.002
	(4.42)	(3.53)	(2.61)	(0.40)	(1.35)	(0.66)
Part-Time Self-Employment	0.153	0.083	0.073	0.198	0.101	0.122
	(18.70)	(12.40)	(11.82)	(24.40)	(15.57)	(17.37)
Part-Time Wage/Salary	0.004	0.004	0.001	0.005	0.005	0.000
	(1.42)	(1.48)	(0.35)	(1.36)	(1.64)	(0.14)
Unemployed	0.012	0.006	0.005	0.016	0.009	0.007
	(4.99)	(3.66)	(3.33)	(5.48)	(4.05)	(3.62)
Welfare	-0.008	-0.004	-0.003	-0.008	-0.006	-0.003
	(7.93)	(6.34)	(4.83)	(5.57)	(5.23)	(2.29)

Not in the Labor Force	0.006	0.003	0.002	0.007	0.005	0.002
	(4.72)	(3.68)	(3.00)	(3.86)	(3.69)	(1.19)
Years at Job	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001
	(9.87)	(6.97)	(6.90)	(6.36)	(3.99)	(4.14)
Years at Job^2/100	0.003	0.002	0.001	0.004	0.001	0.002
	(5.76)	(3.96)	(4.09)	(3.87)	(2.09)	(2.82)
Wald Test of Exogeneity (χ^2)				5.14	3.63	31.97
Number of Observations	144,687	143,487	143,240	144,687	143,487	143,240

Note: Median local housing price is used as an instrument for current net worth. Z-statistics in parentheses. Source: 1996 and 2001 SIPP

APPENDIX

Table A1. Summary Statistics, Sample Means and Standard Errors, Part-Time Self-Employment Entry Sample.

	Entry to Part-Time Self-Employment	
Years of Schooling	14.23	(0.0985)
High School Dropout	0.074	(0.0098)
High School Graduate	0.194	(0.0141)
Some College	0.316	(0.0168)
College Graduate	0.270	(0.0160)
Post College	0.147	(0.0127)
Age	40.1	(0.3402)
Female	0.557	(0.0179)
Married	0.670	(0.0172)
Number of Children	1.039	(0.0444)
Child 5 or younger	0.323	(0.0169)
Non-Hispanic White	0.823	(0.0147)
Hispanic	0.073	(0.0100)
African American	0.067	(0.0103)
Asian	0.013	(0.0041)
Other Ethnicity	0.024	(0.0056)
Immigrant	0.131	(0.0122)
Lagged Variables		
Part-Time Self-Employed	N/A	N/A
Full-Time Wage/Salary	0.657	(0.0173)
Part-Time Wage/Salary	0.040	(0.0069)
Unemployed	0.053	(0.0089)
Welfare	0.026	(0.0064)
Not in the Labor Force	0.225	(0.0151)
Years at Job	3.89	(0.2353)
Household Net Worth	329,733	(168950)
Number of Observations	850	