Effects of Wealth Inequality on Entrepreneurship

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This is an Accepted Manuscript of an article published by Springer in Small Business Economics on 03 May 2016, available online:

http://link.springer.com/article/10.1007%2Fs11187-016-9742-9

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Abstract

This study examines whether personal net worth affects new venture creation and performance. Prior research on wealth and entrepreneurial entry has relied on data providing only a snapshot of the transition into self-employment. The present study draws on a sample of US nascent entrepreneurs actively attempting to start new ventures. Controlling for a number of covariates and the endogenous accumulation of wealth, we find strong evidence of higher dropout rates among low-wealth and moderately wealthy nascent entrepreneurs. However, wealth appears to have no effect on venture creation for those managing to remain in gestation. This suggests liquidity constraints theory applies more toward entrepreneurial disengagement than entrepreneurial entry. Furthermore, the suggestion that the wealthy are able to aggressively grow their ventures is only partially supported by the data when we include a set of covariates correlated with wealth. Integrating these findings, we conclude that entrepreneurial success is concentrated at the top of the wealth distribution, despite notable evidence of capability for those at the lower end of the wealth distribution.

Keywords: Wealth inequality; entrepreneurial entry; nascent entrepreneur; new venture performance; liquidity constraints

JEL Classification: C21, C24, D31, D63, J24, J62, M13

1. Introduction

Low-wealth individuals electing to start their own ventures will likely face significant hurdles during the venture creation process. One such hurdle is the inability to borrow external funds. Financial capital is a vital resource for entrepreneurs attempting to start and grow new ventures (Cassar 2004), yet people with little to no net worth will be unable to draw on accrued savings, or use their wealth as collateral to access credit markets. Economists have investigated this phenomenon under liquidity constraints theory. The theory proposes the decision to become an entrepreneur is contingent on an individual's net worth (Evans and Jovanovic 1989). Low-wealth individuals suffering lower borrowing capacity will be less likely to enter entrepreneurship, and those who do may be unable to grow their ventures (Carter 2011).

Liquidity constraints theory has profound implications for our economy. Consider a low-wealth, nascent entrepreneur attempting to start a business, and let us assume he or she has the necessary skills to transform a good idea into a profitable venture. To the extent the theory of liquidity constraints holds true, this individual's lack of wealth would prevent him or her from transforming a viable opportunity into a successful new venture. And, to the extent this scenario is widespread, entrepreneurship as a means of upward socioeconomic mobility would be limited to those with the prerequisite personal net worth. Indeed, economists have established the wealthiest households are made up by the self-employed (Cagetti and De Nardi 2006; Gentry and Hubbard 2004; Parker 2009; Quadrini 2000). They also dominate the upper echelons of the aggregate wealth distribution—81 % of individuals in the top 1 % self-identify as being a business owner or self-employed (Cagetti and De Nardi 2006). These statistics suggest self-employment may act as a positive facilitator of upward mobility.

Prior research testing liquidity constraints hypotheses offers mixed findings. Some studies suggest credit constraints deter self-employment for individuals with a lower household net worth (Evans and Jovanovic 1989; Fairlie 1999; Gentry and Hubbard 2004; Zissimopoulos et al. 2009). Other studies find the relationship between wealth and entrepreneurship to be flat for the majority of the population (Hurst and Lusardi 2004). A possible explanation for these mixed findings is a failure to account for endogeneity effects resulting from the accumulation of wealth over time. This can occur when (1) the data do not contain measurements of personal wealth taken prior to the decision to enter into entrepreneurialism, and (2) the data do not cover the startup gestation process, prior to the event of successful venture creation. For example, almost all prior research on liquidity constraints draws on large-scale datasets such as the Census Bureau's Survey of Income and Program Participation (SIPP), the Survey of Consumer Finances (SCF), and the Panel Study of Income Dynamics (PSID). While these datasets allow testing of formal models with thousands of cases, respondents self-identify as either an employee, or self-employed, from 1 year to the next. They may not, however, identify as both simultaneously. Yet up to 80 % of nascent entrepreneurs are employed at least part time (Petrova 2012). Many of these respondents may accumulate substantial wealth from their entrepreneurial endeavors before deciding to list themselves as self-employed in a survey. The consequence is an endogeneity problem resulting from wealth accumulation.

Furthermore, the use of self-employment to represent entrepreneurial entry rather than the venture creation process leads to both an underrepresentation of entrepreneurs and a survivor bias. Underrepresentation occurs when survey respondents list themselves only as a part-time employee despite simultaneously working on their own business (Reynolds and White 1997). Survivor bias occurs because many of the self-employed respondents in these surveys have already successfully created a new venture. They are therefore no longer at risk of disengaging from their efforts before the startup is launched. Failure to account for underrepresentation and survivor bias limits the validity and generalizability of research results, and they limit the application of liquidity constraints theory to successful surviving firms. The link between wealth and disengagement from startup gestation remains unexplored.

In this study, we examine the effects of personal wealth on both new venture creation and disengagement. We do so using the Panel Study of Entrepreneurial Dynamics II (PSED II) dataset of 1214 nascent entrepreneurs. The PSED II limits endogeneity effects resulting from the accumulation of wealth by recording each nascent entrepreneur's wealth position in the first year of the panel as the treatment affecting their outcomes in the final year of the panel. Hence, a finding of significant correlation is highly unlikely to be attributable to a reverse causality mechanism. The dataset also limits, if not eliminates altogether, the underrepresentation and survivor biases inherent to data used in prior studies. Recognizing that wealth is only one factor affecting entry into entrepreneurship, we explore important boundary conditions of liquidity constraints theory by constructing a parsimonious model controlling for several dimensions of human capital and industry complexity. Finally, we evaluate new venture performance outcomes by hypothesizing that wealthier entrepreneurs invest larger amounts of capital to grow their firms. This provides us with insight into revenue generation and job creation by nascent entrepreneurs with diverse wealth profiles. On a more fundamental level, this study aims to investigate the extent to which wealth inequality affects entrepreneurship—the engine of economic growth.

2. Wealth and Entrepreneurship

Although it is plausible that wealthy entrepreneurs have no comparative advantage during the process of transforming an idea into a new venture (Parker 2003), in actuality investors often deny loans to low-wealth individuals. This occurs when investors require personal collateral that cannot be provided (Gentry and Hubbard 2004; Banerjee and Newman 1993; Aghion and Bolton 1997). Liquidity constraints theory predicts individuals with inadequate personal financial resources must turn to imperfect credit markets for funding. The absence of wealth then impedes their ability to raise capital. In a study of 1443 men, aged 24–34 from the National Longitudinal Survey of Young Men (NLS), individuals seeking self-employment were limited to raising financial capital stock of up to 150 % of their wealth (Evans and Jovanovic 1989). A number of other studies have found a positive relationship between wealth and self-employment (Blanchflower and Oswald 1990; Fairlie 1999; Gentry and Hubbard 2004; Holtz-Eakin et al. 1993; Quadrini 1999).

2.1. Liquidity constraints and entrepreneurial entry

One drawback to these studies is their focus on entrepreneurs who have already established new ventures. This results in an inherent survivor bias. For those who disengaged from the startup process, little is known about how the lack of wealth affected them beyond the fact that they quit (Parker 2009). Two studies that did investigate the link between wealth and entrepreneurial entry found no observable effect. Data from the PSED I reveal significant entrepreneurial advantages accrued to nascent entrepreneurs with high levels of human capital, but the level of financial capital produced no discernable effect on new venture creation (Kim et al. 2006). And, for nascent entrepreneurs simultaneously working part time (and presumably more wealthy as a result), additional benefits did not accrue either (Petrova 2012). These results imply an absence of liquidity constraints when studying entrepreneurship during the gestation process, before a new venture is launched.

Studies on liquidity constraints have also sought ways to address endogeneity resulting from the acquisition of wealth over time. Some individuals will accumulate wealth during the startup gestation period. To control for this, researchers must either identify an instrumental variable, or measure wealth at time ‘‘0’’ before the decision to enter into startup gestation was made. An example of the use of instrumental variables involves windfalls such as inheritances or lottery winnings. The sudden injection of such wealth might induce an individual to enter into entrepreneurialism. Prior research has shown a $150,000 inheritance produces a 20 % increase in a new venture's receipts, leading to a higher probability of survival (Holtz-Eakin et al. 1993). This suggests that wealth is indeed a factor in occupational choice.

Endogeneity also arises when the wealth variable captures unobserved attributes, such as higher levels of human capital that correlate with both entrepreneurship and wealth (Parker 2009). Higher levels of education or managerial experience can lead to greater experience and improve the likelihood of successfully starting a new venture. They can also result in higher income. Even the use of inheritances as an instrumental variable can introduce problems because an inheritance may not be a truly exogenous event. The individuals receiving them are more likely to come from wealthy families possessing strong social networks (Lofstrom et al. 2014). Lottery winnings are linked to neither human nor social capital, however. Lottery winners have been found to increase the propensity for entrepreneurial entry by 54 % in Sweden (Lindh and Ohlsson 1996). Yet another instrumental variable is housing price appreciation. Research has shown that entry rates appear virtually flat for all individuals between the 1st and 95th percentiles in wealth distribution, with a discernible and steep relationship only above the 95th percentile of wealth (Hurst and Lusardi 2004).

Investigating subsamples of respondents who are likely to be more or less wealthy due to extenuating circumstances can also control for wealth endogeneity. For example, individuals who are gainfully employed at the time of making the decision to enter into entrepreneurialism are likely wealthier than unemployed individuals. This latter group has been termed ‘‘job-loss’’ entrepreneurs in that their decision to enter into entrepreneurialism is likely driven by having lost a wage or salary position (Fairlie and Krashinsky 2012). Studies investigating this group have found job-losers to be less wealthy. It is therefore necessary to control for these factors when investigating wealth effects.

Wealth may also affect entrepreneurialism differently during gestation. This context covers both the duration and heterogeneity inherent to the nascent process. Nascent entrepreneurs use their wealth during gestation to maintain the venture’s viability and to avoid disengagement (Gartner et al. 2012; de Meza and Southey 1996). There is also a great deal of variation in the types of opportunities nascent entrepreneurs pursue. Many might be considered part of the ‘‘modest majority’’ of ventures that do not require large financial investments during gestation (Davidsson and Gordon 2012). Others require large investments in land, location, and equipment. Taking these factors into account, we theorize that higher levels of wealth provide startups with a cushion against unforeseen events, and we directly test the relationship between organizational emergence and wealth with the following hypotheses:

Hypothesis 1a: Low-wealth nascent entrepreneurs are more likely disengage from the startup process, compared to wealthier nascent entrepreneurs.

Hypothesis 1b: Among those nascent entrepreneurs who remain engaged in the startup process, low-wealth nascent entrepreneurs are less likely to create new firms, compared to wealthier nascent entrepreneurs.

2.2. Performance measures, wealth, and entrepreneurial entry

A central theme of studies on economic well-being and rising standards of living is entrepreneurship as a driver of GDP and employment growth (Landes et al. 2012). In the US economy, new venture creation has been linked to job growth and innovation (Acs 2008; Acs and Audretsch 1988; Birch 2000). It is reasonable to assume wealth may influence these outcomes. Although little evidence of such a relationship has been presented to date, there are hints a positive relationship exists. For example, ‘‘job-creating’’ entrepreneurs in Great Britain possess 80 % more housing wealth than sole proprietorships (Henley 2005). This implies housing wealth may provide collateral for loans, spurring venture growth and influencing job creation. Prior research also suggests the entrepreneur plays a pivotal role in generating employment, innovations, and fostering informational spillovers (Van Praag and Versloot 2007).

Past research has also examined how wealth influences the rewards that may accrue from entrepreneurship. ‘‘Rewards’’ include revenue earned from the venture, which is essentially a performance measure. Low-wealth individuals may leave wage or salaried employment and enter into entrepreneurialism in search of greater financial rewards (Carter 2011; Evans and Leighton 1989; Rees and Shah 1986). However, once in the gestation process, they may be unable to grow the venture (Freel 2007; Stiglitz and Weiss 1981). We propose that the mechanism by which wealth might influence new venture performance is rooted in the belief that entrepreneurship will provide greater financial rewards compared to regular employment. Once the decision to enter into entrepreneurship has been made, those with a lower personal net worth will experience difficulties attempting to grow their business. Based on the above studies, we suggest two proxies to represent the level of new venture performance—the amount of revenue earned in the first year of operations, and the number of employees hired. We test the impact of wealth on new venture performance via the following hypotheses:

Hypothesis 2a: Among those nascent entrepreneurs who have started a new firm, low-wealth nascent entrepreneurs will earn less revenue in the first year of operation compared to wealthier nascent entrepreneurs.

Hypothesis 2b: Among those nascent entrepreneurs who have started a new firm, low-wealth nascent entrepreneurs will hire fewer employees in the first year of operation compared to wealthier nascent entrepreneurs.

3. Methodology

3.1. Research setting

Startup gestation is an ideal setting for examining the effects of wealth on entrepreneurial entry. It allows us to measure true entry into entrepreneurship because we are examining startup activities before a venture is actually created. Gestation is the period when nascent entrepreneurs are transitioning from attempting to start a business to actually launching a new venture, or disengaging from the process. With the exception of only a few studies (Kim et al. 2006; Petrova 2012), prior research on wealth and entry has not addressed this transition. Instead, studies have relied on large-scale datasets that record an individual's change in employment status from 1 year to the next, but not the venture creation process itself.

The Panel Study of Entrepreneurial Dynamics (PSED) research program was designed to fill a specific gap. No other program captures the startup gestation period of the startup process on a scale that is generalizable to the entire economy, and none provides comparisons between nascent entrepreneurs who succeed and those who disengage (Reynolds 2000). The PSED II is a representative sample of 1214 US working-age adults who were actively engaged in creating new ventures between 2005 and 2012. The first step toward identifying nascent entrepreneurs for this sample was a nationwide screening process. Between October 2005 and January 2006, a commercial survey firm used random digit dialing to screen 31,845 individuals. Those meeting the following four criteria were considered nascent entrepreneurs and included in the final sample: (1) They considered themselves as involved in creating a firm, (2) they had completed at least one startup activity in the past 12 months, (3) they expected to own all or part of the new firm, and (4) their efforts had not resulted in an operating business. These 1214 nascent entrepreneurs completed 60-min phone interviews administered by the University of Michigan Institute for Social Research. The interviews were conducted in 1-year intervals across six waves of data (Reynolds and Curtin 2007).

The data are well suited to our investigation into personal wealth and entrepreneurial entry. First, the primary objective of the PSED research program is to provide systematic and reliable data on nascent entrepreneurs attempting to start new firms. This allows us to accurately measure the rate of transition from not having a business, to operating a business in the US economy. Second, the PSED includes variables that explain and predict variation in this transition (Reynolds 2000). These variables include measures of personal wealth, human capital, demographic information, and activities that make up the firm creation process.

We arrived at the final sample size for each model in the following manner: models 1 and 2 (Hypothesis 1a) = 1025 (from the 1214 cases in the original data file, 7 are removed because a new venture was formed prior to the initial wave of data collection; 41 respondents did not report their household net worth; 1 outlier is removed, a case where a low-wealth nascent entrepreneur hired 200 employees; 102 respondents did not participate in the follow-up interviews after the screener; and 39 cases represent missing values among one or more of the covariates predictors); models 3 and 4 (Hypothesis 1b) = 508 and 494, respectively. This is the subsample of respondents who have not disengaged, but have remained in gestation or created a new venture: models 5a, 5b, 6a, and 6b = 245, 218, 250, and 243, respectively. This is the subsample of respondents who created new ventures. The variations in sample size result from missing values among one or more of the covariate predictors.

We weight all analyses in this study to align the PSED II sample to the US Department of the Census Current Population Survey. This ensures the generalizability of our findings to the population of nascent entrepreneurs in the USA. Initial weights for each respondent were provided by ORC International at the time of the initial screening interview. The University of Michigan Survey Research Center reconfigured the weights to reduce variation among cases, and we renormalized the weights for each regression model so that the sum of weights equaled the number of individuals in the subsample of interest (Shaver et al. 2015).

3.2. Methodological strategy

Prior studies have found that wealthy individuals are more likely to report switching from wage work 1 year, to self-employment the next (Evans and Jovanovic 1989; Holtz-Eakin et al. 1993; Xu 1998). This creates potential endogeneity and sample selection problems. If wealthy individuals are more likely to attempt entrepreneurship, then entrepreneurs are more likely to be wealthy. Furthermore, if successfully starting a business adds to household wealth, then wealth measures will be biased upward. We address these issues by employing the following methodological strategy:

First, we carefully consider the timing of our measures of wealth and performance outcomes as part of our identification strategy for dealing with endogeneity. Wealth is measured in 2005 when there is no venture, and startup performance outcomes are measured in later years after a new venture is created. This reduces endogeneity bias, if not eliminating it altogether. Additionally, it is unlikely that respondents in the sample have accumulated significant wealth from their ventures as of 2005, since the ventures themselves are not yet up-and-running.

Second, we are not investigating the decision to enter into entrepreneurialism, but rather the outcome of such efforts after the decision has been made. Our sample of nascent entrepreneurs is representative of the US population of individuals attempting to start ventures between 2005 and 2012. At some point during this gestation period, every respondent in the sample will be in one of the three states: having started a new venture, having disengaged from the process, or still trying to start a business through the end of the sampling time frame.

Third, we incorporate a number of covariate predictors to further reduce wealth-related endogeneity. Prior studies have included these variables, as they are likely to influence the relationship between wealth and startup outcomes. The covariate controls that we utilize are team size, the number of non-owner helpers, the amount of personal funds invested, whether the respondent was gainfully employed upon entry, the type of startup (franchise, takeover of an existing business, etc.), industry complexity, education, race, and sex.

Finally, we distinguish between those who are engaged in nascent entrepreneurship and those who disengage. This allows us to focus on whether the amount of personal wealth (as well as other predictors) affects the decision to abandon the nascent venture during gestation. Because we expect that disengagement does not occur randomly, we estimate Hypothesis 1 using two regression models: one examining the effects of wealth on disengagement versus nondisengagement for the entire PSED II sample, and one examining the effects of wealth on new venture creation among the subsample of respondents who have not quit. This structure covers the probability of being in each of the three states. Our design carefully controls for the amount of time each respondent remained in the gestation phase. Prior work has found nascent entrepreneurs remaining in gestation for long periods differ from other nascent entrepreneurs, most notably by the amount of effort contributed during gestation (Reynolds and Curtin 2009).

3.3. Dependent variables

3.3.1 Startup outcome

OUTCOME is coded as ‘‘1’’ for nascent entrepreneurs who disengaged during startup gestation and ‘‘0’’ for those who remained in gestation and/or started a new firm. The PSED II defines startup outcomes in the following manner (Reynolds and Curtin 2008): New Firm = income was received in 6 of the past 12 months, covering all expenses, including owners’ wages and salaries; Still Trying = the nascent entrepreneur devoted more than 160h in the past 12 months to the startup, and he or she expected to spend 80 or more hours in the next 6 months on the startup; Quit = answering ‘‘Yes’’ to the question, ‘‘Would you consider yourself disengaged from the business effort discussed a year ago?’’ NEW FIRM is coded as ‘‘1’’ for nascent entrepreneurs who successfully started a new firm and ‘‘0’’ for those who remained engaged without quitting for the duration of the sample period. This variable measures the likelihood of starting a new firm given sustained engagement in the entrepreneurial process.

3.3.2. New firm revenue and number of employees

REVENUE measures the total revenue earned by successful new ventures in their first year of operation. Respondents were asked to report total revenue from the sale of goods, services, or intellectual property in the past 12 months. *EMPLOYEES* measures the number of employees hired by successful new ventures in their first year.

3.4. Treatment variable

WEALTH is a multi-item measure that calculates the respondent's household net worth. Respondents were asked about the market value of their primary residence, how much was still owed on the mortgage (if applicable), an estimate of all household savings and investments (e.g., value of stocks, bonds, mutual funds, savings accounts, checking accounts, retirement accounts, non-incorporated business assets, etc.), the value of miscellaneous assets (e.g., other real estate, cars, boats, home furnishings, jewelry, etc.), the amount of all outstanding loans that use the primary residence as collateral, and an estimate of all other debts of all members of the household (e.g., loans, land contracts on other property, home equity loans, automobile loans, credit card balances, education loans, etc.).

Respondents were then asked to verify the calculated amount. If this matched the survey administrator's calculations, the amount was recorded. If not, the above sequence of questions was repeated until the amounts matched. Of the 1214 respondents, 41 respondents (3.3 %) did not report their net worth, and 167 (13.8 %) opted to report a bracketed rather than an exact dollar amount for their net worth. We imputed the midpoint dollar amount in these cases. For example, respondents reporting a net worth of $100,000–$249,999 were recorded as $175,000.

We then divided the WEALTH variable into tertile dummies—three variables taking on a value of 0 (not in this group) or 1 (belongs to this group), representing the following tertiles in the wealth distribution: bottom tertile (beneath the 33rd percentile); middle tertile (between the 33rd and 66th percentile); and top tertile (above the 66th percentile). Measuring wealth in tertiles allows us to conduct research into liquidity constraints with nonlinear effects at disparate wealth levels using post-2000 data from the PSED II. It also allows us to harness the data's limited power to identify whether liquidity constraints apply around specific levels of wealth. This could lead to a concern that the cutoffs in the wealth distribution are made arbitrarily. We have addressed this concern utilizing a number of econometric techniques that are described below.

3.5. Additional control variables

TEAM controls for the effects that the household wealth of other team members may have on the venture. The PSED II does not provide the net worth for all members of the startup team, but we are able to separate solo efforts and spousal teams from other startup teams. This variable is coded as ''0'' for solo or spousal teams and ''1'' for teams of non-spousal teams of two or more. Similarly, we also control for the number of non-owner helpers who have provided significant support. NON-OWNER HELPERS is a continuous variable measuring the number of helpers given by the respondent. GAINFULLY EMPLOYED controls for differences between ''job-loss'' and ''non- job-loss'' nascent entrepreneurs (Fairlie and Krashinsky 2012). We code this variable as ''1'' for those gainfully employed elsewhere as nascent entrepreneurs and ''0'' for those who are not. We control for the amount of personal money invested in the venture since prior research has found wealthier individuals invest more of their own money. PERSONAL FUNDS INVESTED is measured as the total amount of personal savings the respondent invested in the venture. We control for BUSINESS TYPE by using a categorical variable coded as ''0'' for an independent new business; ''1'' for purchase/takeover of existing business; ''2'' for franchise; ''3'' for multi-level marketing scheme; and ''5'' for a new business sponsored by an existing business. A new business that is sponsored by an existing business, for example, would likely reduce the need to tap into one's personal wealth.

We control for INDUSTRY COMPLEXITY to account for the complexity of the business opportunity. Industry is a binary variable coded as ‘‘0’’ for non-complex, or routine ventures, and ‘‘1’’ for complex ventures. Complex industries likely require greater investment prior to launch, and they have different rates of entry (Lofstrom et al. 2014). Startups requiring a dedicated location command more financial investment compared to ventures that are more modest in nature and operated from the founder’s primary residence (Davidsson and Gordon 2012). To assess venture complexity during gestation, we combine a number of variables from the PSED II to create our industry control variable. Respondents were first asked what kind of business they were starting. These responses were coded using the North American Industry Classification System to six digits—economic sector (digits 1 and 2); subsector (digit 3); industry group (digit 4); NAICS industry (digit 5); and national industry (digit 6). The NAICS code is insufficient for assessing complexity, however. Consider two ventures, both recorded as ‘‘jewelry manufacturing.’’ One venture is an individual making costume jewelry at home, while the other has multiple locations and requires large equipment purchases. We therefore further consider both the venture’s locational needs (i.e., whether it is located within the primary residence or one or more separate, physical locations), and whether any major items like equipment, facilities, or property have been purchased. An example of a complex venture is respondent 50020 attempting to start a commercial printing business at a specific, non-residential location. An example of a more routine venture is respondent 50025 making children’s clothing from a residential location. A separate data file was created including each respondent’s answers to these survey items in the PSED II. We then independently coded each case as either complex or routine. Results indicated an interrater reliability (IRR) estimate of 0.88 consistency.

Prior research indicates that organizational emergence is a function of higher levels of human capital (Davidsson and Honig 2003). An individual's education, prior experience as an entrepreneur, or managerial experience affects the likelihood of successfully starting a business (Bates 1990; Davidsson and Honig 2003). We measure EDUCATION as the level of education (1 = below high school; 2 = high school; 3 = some college; 4 = bachelors; 5 = graduate school); PRIOR STARTUPS as the number of prior startups the respondent helped start; and MANAGERIAL EXPERIENCE as the number of years of managerial or supervisory experience.

An individual's network of relationships, past and present, can assist them in creating and growing a business through access to resources and customers (Florin et al. 2003; Liao and Welsch 2005). Our measure of COMMUNITY SUPPORT is a four-item subscale that asks respondents to rate their agreement on a scale of 1–5 (1 = strongly agree; 5 = strongly disagree) with the following: (1) ‘‘Young people in your community are encouraged to be independent and start their own businesses.’’ (2) ‘‘State and local governments in your community provide good support for those starting new businesses.’’ (3) ‘‘Bankers and other investors in your community go out of their way to help new businesses get started.’’ (4) ‘‘Community groups provide good support for those starting new businesses.’’ Table 1 shows that Cronbach's alpha for the four perceived community support items is reliable (a = 0.70).

INSERT TABLE 1 ABOUT HERE

We also control for the race and sex of the nascent entrepreneurs in our sample. Females tend to have lower risk profiles than males, and their startups tend to be smaller (Fairlie and Robb 2009). Prior studies have also found links between startup capital requirements and race, with Asian-owned firms outperforming ventures started by other races (Fairlie and Robb 2008; Robb and Watson 2012). African-Americans have also been found to have longer transition times and much lower rates of emergence. The longer waiting period for minorities may suggest evidence of further borrowing constraints (Parker and Belghitar 2006). In our study, SEX is coded as 0 = female, and 1 = male; and RACE is coded as 1 = Caucasian; 2 = African-American; and 3 = other.

Finally, we control for TIME in gestation, as prior studies have found that nascent entrepreneurs remaining in gestation for long periods differ from other nascent entrepreneurs along a number of dimensions, including the amount of effort contributed during gestation (Reynolds and Curtin 2009).

3.6. Models and estimation procedures

A series of regression models are used to determine the impact of wealth on (1) the likelihood of disengaging from the startup gestation period, continued engagement, or successful new venture creation; and (2) the performance of new ventures in their first year of operation as measured by revenues and the number of employees hired. Cox survival regression is used to test Hypothesis 1a since we are interested in the hazard (i.e., risk) of disengagement during gestation. Our Cox regression provides estimates of how much wealth increases or decreases the likelihood of disengagement during gestation, before a new venture is created. This explicitly addresses the strong presence of left truncation bias in the PSED II dataset due to nascent startups being at high risk of abandonment.[1]

Binary logistic regression is used to test Hypothesis 1b since our outcome of interest is the probability of successfully launching a new venture given that nascent entrepreneurs did not disengage. OLS regression is used to test Hypothesis 2a because the outcome is first-year revenues (a continuous variable), and Poisson regression is used on Hypothesis 2b because the

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[1] As of the first interview in the PSED II, each venture had been at risk of termination for a period of time, resulting in left truncation—that is, the sample contains only firms that survived the period between first activity and the first interview, and strong emerging organizations may be overrepresented (Yang and Aldrich 2012).

outcome, first-year employee hires, is count data where the event of hiring an employee is relatively rare. In all models, we follow a strategy used by Liao and Gartner (2006) by first creating a base regression model that includes our control variables, and those variables identified in prior literature known to correct for wealth-related endogeneity problems. We then add our wealth variable and use a Chi-square test to determine whether there is a statistically significant difference between the full and base models. A significant test means adding wealth as a predictor explains additional variance in the probability of the outcome of interest.

4. Results

4.1. Descriptive statistics

Nascent entrepreneurs tend to be wealthier than the US general population. Table 2 and Fig. 1 depict the empirical distributions of net worth among nascent entrepreneurs in the first wave (2005) of the PSED II (the dashed line with 90 % confidence bands in gray) and corresponding percentiles for the general population from the US Census Bureau's 2005 Survey of Income and Program Participation (as dots with horizontal whiskers indicating a 90 % confidence interval, which is so small that it is difficult to discern at this scale).[2]

INSERT TABLE 2 AND FIGURE 1 ABOUT HERE

Because net worth among nascent entrepreneurs tends to be higher than the general population, we see the first hint that the enterprise of entrepreneurialism might be more favorable for the wealthy—they are more likely to make the decision to start a business (and we presume that low-wealth individuals are less likely to try due to a lower return on their investment, to the

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[2] Two features of the graph are worth noting. First, the horizontal scale has been limited to -$100,000 and $1,000,000 so that we can focus on the data's centrality—the top 8 % and lower 1 % both extend far beyond those limits and dwarf the remainder of the graph. Second, six steep vertical climbs in the (blue) empirical distribution function for the PSED II occur due to those few observations where a unique value for net worth was withheld by the respondent so that we had to impute net worth as the midpoint of the range provided by the respondent.

extent that they can invest).[3] As can be seen in Fig. 1, the distributions overlap at the 10th percentile where net worth among both nascent entrepreneurs and the general population is slightly below $0. At the higher percentiles observed in the SIPP, the wealth of nascent entrepreneurs is significantly higher than the general population. Therefore, we conclude that nascent entrepreneurs tend to have a higher net worth than the general population.

We also observe that, without any consideration for covariates or sophisticated treatment of nonlinearity or even uncertainty in inference, wealthy nascent entrepreneurs are more likely to start new ventures in the raw data. Table 3 shows that the ratio of new venture creation to disengaging is nonlinear, with one venture created for every three who disengage until around the 66th percentile of the wealth distribution where disengagement becomes conspicuously less common. Here, the odds of starting a new venture roughly double—we see two successful attempts for every three that disengage. These simple summary statistics provide preliminary support for Hypothesis 1 in the next section.

INSERT TABLE 3 ABOUT HERE

4.2. Preliminary analyses

We test our hypotheses by applying a battery of tools to gauge the robustness of the results from the simple cuts of the raw data above. We explicitly consider the presence of uncertainty in a more formal inference, employing a variety of sophisticated treatments of nonlinearity and the influence of confounding covariates. While the potential importance of confounding from correlated covariates should be self-evident, we nonetheless present the correlation matrix for the key variables in this study in Table 4. Correlations greater than 0.1 are italics. Severe multicollinearity should not be a problem affecting our analyses; when we include

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[3] If one envisions that starting any business requires a minimum amount of investment that is beyond the means of low-wealth individuals, then this can be recast as a -100 % rate of return on an investment beneath that threshold.

covariate controls, there should be an adequate amount of remaining variation to allow us to identify significant effects in both our treatment and control covariates.[4]

INSERT TABLE 4 ABOUT HERE

Before considering the role of confounding covariates, we first run a regression on tertile dummy variables to formally ascertain the uncertainty of the pattern that we have detected in the raw data. To address concerns over whether splitting our wealth variable into tertiles is arbitrary, we generalize the approach in several ways to gauge the robustness of our results. As to the general problem in econometrics, we face a trade-off between (a) imposing more structure on the functional form to extract more information from the available data so that we can better identify any significant effects, and (b) imposing less structure so that the data identify the functional form, but then less information is available in the data to identify the significance of any effects.

Tertile dummies make virtually no assumption on functional form, other than an assumption that those cutoffs are sufficient to see any significant differences in the relationship between an outcome variable and wealth percentile over the whole continuum of percentiles. This generates two concerns. First, one could be concerned that we ‘‘cherry-picked’’ the cutoffs, thus obscuring some more interesting underlying relationship. Second, one could be concerned that a significant relationship has simply not been detected because not enough structure has been imposed on the functional form to extract all signal from the data. We have addressed the first concern by generalizing the tertile dummies (tertile dummies are, in a technical sense, zeroth-order B-splines) into a continuous curve that reveals the heterogeneity of effects within tertiles into knots of cubic B-splines, which fit a cubic polynomial within each tertile subject to

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[4] The Variance Inflation Factor for each variable is less than 10, with a mean VIF of around 1.14 for each model. We are therefore confident our regression models do not suffer from multicollinearity.

the restriction that the estimated cubic segments have the same height (and slope and curvative) when they meet at each knot.[5]

We also address concerns over the strategic selection of dummy cutoffs by treating wealth percentiles as a continuous variable (i.e., each observation is assigned the rank of its net worth in the sample divided by the total number of observations) and regressing outcomes directly on the percentile of the wealth distribution. This provides a parsimonious test of each hypothesis with a single parameter. This approach (i.e., using a [0, 1] percentile measure as the treatment variable) is preferred to regressing outcomes on the actual value of net worth (i.e., using a dollar measure as the treatment variable) because it is more robust to outliers in the highly skewed wealth distribution and also somewhat more comparable to our simple descriptive statistics using tertiles. Because this approach makes a strong assumption (linearity) on the relationship between the percentile and outcome, this approach extracts the most amount of information available in the data (for that structure) and hence is most likely to identify any sort of significant signal in the available sample of modest size.

Because treating percentiles as a continuum assumes a linear relationship between the percentile and the outcome, we have also generalized the results by examining a purely nonparametric loess smoother that can capture any sort of nonlinear relationship, so long as the relationship is continuous and therefore entirely free of any functional form specification.[6]

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[5] This should reveal any hidden underlying nonlinear relation- ship, but nothing noteworthy emerges (and hence the results have been suppressed from our plots for clarity).

[6] The loess method uses weighted least squares to fit the regression for each wealth percentile ‘‘section’’ overlaying the regression, weighting data points with a decreasing function of their distance from the wealth level being plotted (Garson 2012). Nonparametric estimation of a nonlinear function is appropriate here given our preliminary observations of the nonlinear effects of wealth on nascent entrepreneur outcomes, at the individual and firm level. These effects mirror those found in structural inequality at the societal level (Piketty 2014).

Again, because the nonparametric alternative revealed we did not miss much of interest with our simpler methods, we have suppressed those results from the plots for clarity.[7]

4.3. Regression results

4.3.1. Cox regression of wealth on the risk of disengaging from startup gestation

Hypothesis 1a. In Hypothesis 1a, we argued that low-wealth nascent entrepreneurs would more likely disengage during startup gestation. Model 1 of Table 5 shows some positive and significant coefficients for some covariates: team, the type of business, and perceived community support. This suggests nascent entrepreneurial teams of two or more individuals are 26 % more likely to disengage during gestation than solo nascent entrepreneurs or spousal teams. Nascent entrepreneurs attempting to start a franchise or multilevel marketing/sales business are 77 and 84 % more likely to disengage compared to independent ventures. And, those operating in communities with low support for entrepreneurs are 10 % more likely to disengage rather than remain in gestation or start a new venture. Gainful employment and race have significant, negative coefficients. This suggests individuals entering into startup gestation while gainfully employed are 30 % less likely to disengage during gestation, and African-Americans are 40 % less likely to disengage compared to Whites. Managerial experience, while statistically significant, is not substantively significant with an odds ratio practically equal to 1.

Model 2 of Table 5 shows the coefficient for the bottom wealth tertile is 0.3779 ($p < 0.01$) and the middle tertile is 0.2459 ($p < 0.05$), with odds ratios of 1.46 and 1.28, respectively, controlling for covariates. Nascent entrepreneurs in the bottom tertile of the wealth distribution are 46 % more likely to disengage than those in the top wealth tertile, and those in the middle tertile are 28 % more likely to disengage than those at the top. Hypothesis 1a is therefore

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[7] However, because this approach makes the fewest assumptions on functional form, it is most susceptible to noise in the available sample of modest size.

supported. Model 2 also tests the independent effect of wealth on disengagement. The additional explanatory power provided by adding the wealth tertile dummies to Model 1 is statistically significant.

Figure 2 depicts this relationship graphically. The dashed line represents a continuum measure of wealth with 90 % confidence interval around it in gray. The three, vertical error bars represent the tertile dummies with a 90 % confidence interval for the width of each tertile.[8] The probability of disengaging in the lowest wealth tertile is between approximately 50 and 60 % (the vertical bands), without controlling for any covariates. We also see nascent entrepreneurs in the bottom tertile are 46 % more likely to disengage than those in the top wealth tertile. Disengagement does not vary much between the bottom and middle tertile where we observe significant overlap in confidence intervals. The probability of disengagement by the wealthiest nascent entrepreneurs is between approximately 35 and 45 %. The coefficient on the net worth variable is significant (regardless of whether we utilize covariate controls), implying strong evidence that those with lower net worth are likely to disengage from startup gestation.

INSERT TABLE 5 AND FIGURE 2 ABOUT HERE

4.3.2. Logistic regression of wealth on new venture creation

Hypothesis 1b: In Hypothesis 1b, we argued that, among those who do not disengage during startup gestation, low-wealth nascent entrepreneurs would be less likely to start new firms. Model 3 of Table 6 shows the team coefficient has significant, positive effects. This suggests among those that have not yet disengaged, nascent entrepreneurial teams of two or more

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[8] We also conducted semi-parametric and nonparametric tests to gauge the robustness of our results, given the amount of structure that we impose on the data. To facilitate interpretation of the Figures, the cubic splines, knots, and loess smoothers from these tests were removed. Additionally, the horizontal scales on each Figure are limited to range from -$100,000 to $1,000,000 so that we can focus on the data's centrality—the top 8 % and bottom 2 % of nascent entrepreneurs in the wealth distribution extend far beyond those limits and dwarf the remainder of the Figure. The actual data points have been suppressed from the plots because they all fall along the horizontal lines at 0 and 1.

(non-spousal) are almost twice as likely to start a new venture. Race and sex have significant, negative coefficients, suggesting that among those who did not disengage, African-Americans are 60 % less likely than Whites to start new ventures, and males are 35 % less likely than females to start new ventures.

Model 4 of Table 6 shows the coefficients for the bottom and middle wealth tertiles are individually not statistically significant, which is true regardless of whether we control for covariates. The wealth tertiles are also not jointly statistically significant. Wealth does not appear to explain additional variation in the probability of new venture creation among nascent entrepreneurs who did not disengage during gestation. Hypothesis 1b is therefore not supported.

Figure 3 shows the probability of successfully starting a new venture for those who did not disengage during gestation. Across all percentiles (the dashed line within the 90 % uncertainty band in gray) and all tertiles, the probability of starting a new venture remains at or near 50 %.

INSERT TABLE 6 AND FIGURE 3 ABOUT HERE

4.3.3. OLS and Poisson regressions of wealth on first-year revenues and employee hires

Hypothesis 2a. In Hypothesis 2a we argued that low- wealth nascent entrepreneurs who successfully launch new ventures would earn lower first-year revenues compared to wealthy, successful nascent entrepreneurs. Model 5a of Table 7 shows the coefficients for team, personal funds invested, gainful employment, and business type are positive and significant. First- year revenues are: 2.12 times higher for non-spousal teams of two or more compared to solo entrepreneurs or spousal teams (dependent variable is the log of REVENUE, so e 9 0.7801 = 2.1205); 35 % higher for every $100,000 in personal funds invested during gestation; 77 % higher for individuals gainfully employed at entry into gestation compared to unemployed individuals; and 3.60 times, 2.65 times, and 69 % higher for takeovers of existing ventures, franchises, and efforts sponsored by existing firms (respectively), compared to independent ventures. Race has a significant, negative coefficient, suggesting that first-year revenues from new ventures started by African-Americans and Asians/Hispanics will be twice as low compared to revenues from new ventures started by Whites.

Model 5b of Table 7 shows the coefficients for the bottom and middle wealth tertiles are not statistically significant when we control for covariates. In a joint test, the bottom and middle wealth tertiles do not explain a significant amount of additional variation in the amount of first-year revenues among nascent entrepreneurs who successfully started new ventures. Yet, we have already described existing literature finding wealth to matter in growing the new venture. When we examine wealth and revenue alone, a different picture emerges. Figure 4 depicts this relationship graphically, without controlling for covariates. When personal wealth is taken as the sole predictor, we see that first-year revenues are significantly higher for successful nascent entrepreneurs in the top wealth tertile. First-year revenues for the wealthiest are between approximately $75,000 and $100,000. Revenues for the lowest and middle tertiles are between $45,000 and $75,000. When we consider both the semi-parametric cubic splines and nonparametric loess smoothers (not depicted), we find that the curves closely follow a similar path. Taken together, these results do provide some support for Hypothesis 2a, but that support is weak due to the drop in significance when we include covariate controls. This loss of significance is due to the combination of 2 factors: strong correlation between wealth and our covariate controls and the few observations we have for successful new ventures (just over a couple hundred values for revenue in the first year are observable because that is the number of new firms that have been formed). Therefore, we are not comfortable with a blanket rejection of

Hypothesis 2a; there is some weak evidence in our data that revenues decrease as personal wealth decreases, although some confounding variables may actually be the causal drivers for this correlation between revenue and personal wealth. Ultimately, our sample size is simply too small to separately identify the effects for personal wealth and the closely correlated confounders included in our model for revenue.

INSERT TABLE 7 AND FIGURE 4 ABOUT HERE

Hypothesis 2b. Hypothesis 2b argued that low- wealth nascent entrepreneurs successfully launching new ventures would hire fewer employees compared to the wealthy. Model 6a of Table 7 shows the coefficients for team, personal funds invested, business type, industry, and race are positive and significant. This implies that first-year employee hires are: 3 times higher for non-spousal teams of two or more compared to spousal teams and solo entrepreneurs; 24 % higher for every $100,000 of personal funds invested during gestation; 3.47 times and 1.78 times higher for franchises and ventures sponsored by existing firms compared to independent new ventures; and two times higher for successful African-Americans and Asians/Hispanics compared to Whites. Community support has a coefficient that is negative and significant. This is interpreted as successful nascent entrepreneurs perceiving high levels of support within the community hire 2.47 times more employees for their new ventures than those perceiving low levels of community support.

Model 6b of Table 7 shows the coefficients for the bottom and middle wealth tertiles are not statistically significant when we control for covariates. Jointly, the wealth tertile dummies do not explain a significant amount of additional variation in the number of employees hired by nascent entrepreneurs starting new ventures. Given our results for revenue, this is not entirely surprising; revenue is a continuous outcome variable and thus more informative than a discrete count of employees hired. Thus, the relationship between the number of employees and founder's net worth is actually quite noisy. In Fig. 5, we see the results for a specification of tertile dummies without covariate controls. The top tertile appears to hire significantly more employees than the bottom and middle tertiles when we do not include controls. In our full Poisson regression model with all of the covariate controls, however, our parameters appear to have reasonable magnitude but no statistical significance. This is not surprising given how noisy the relationship is (and how uninformative count data tend to be for such a small sample size). Again, our only evidence supporting Hypothesis 2b is tenuous and we are reluctant to make any conclusions beyond that weak support.

INSERT TABLE 7, FIGURE 4, AND FIGURE 5 HERE

4.4 Post-hoc analyses

We conducted a post hoc analysis to gauge the sensitivity of these results to the respondents' self-reported reasons for disengaging. We surmised that if liquidity constraints affect disengagement, then respondents would also report money-related issues as being the main driver of their exit decision. Of the 623 nascent entrepreneurs who disengaged, 57.5 % report money-related problems as their main reason for quitting (e.g., low sales, low cash flow, inability to acquire funds); 33.4 % report personal reasons (e.g., health or family problems); and 9.1 % decided to pursue another opportunity (e.g., education, another startup, or employment). We also checked the sensitivity of our main results to respondents' reasons for disengaging. Informally, it appears to use that wealthier nascent entrepreneurs are less likely to report quitting due to money-related issues compared to low-wealth and middle-class nascent entrepreneurs. Although this lends further support to the liquidity constraints hypothesis, we have not presented a formal analysis of their reasons for quitting here.

Some prior research has shown it is at the top, 95th percentile where we find a steepening relationship between wealth and entrepreneurial success (defined as entry into self-employment) (Hurst and Lusardi 2004). We therefore conducted a post hoc analysis of each regression model after removing those cases at or above the 95th percentile. The results from each of our regression models did not change when removing these cases. Indeed, we took the additional step of removing cases the bottom 5th percentile because of their large amounts of negative net worth (indicating that these individuals are, or recently were, people who we would anecdotally consider to be wealthy individuals). Again, our results did not change.

5. Discussion

This study examined whether low-wealth, nascent entrepreneurs in the USA face liquidity constraints during startup gestation and are therefore more likely to disengage from entrepreneurialism than the middle class or wealthy. It also looked at the effect of personal wealth on the early performance of successful new ventures surviving the startup gestation period. Results indicate low-wealth and moderately wealthy nascent entrepreneurs face liquidity constraints and are significantly more likely to disengage from the startup process during gestation. However, once that hurdle is passed, wealth has no discernable effect on successfully launching a new venture. When further examining wealth's effects on performance of successful new ventures, wealth did not explain variance beyond team effects, human capital, and personal resource investments in the venture. Taken together, these results suggest low-wealth and middle-class nascent entrepreneurs are just as capable as the wealthy, but suffer more from liquidity constraints. Given that new firms create from 20 to 50 % of net new jobs and almost all net jobs (Acs and Armington 2004; Wiens and Jackson 2015), these findings expose a potential divergence where talent is evenly distributed in society, but opportunity is not. We make this assertion with care because we recognize the reduced size of the subsample of new firms may cause a loss of significance in our models examining performance. Nevertheless, these results suggest ''early impact'' new ventures, as measured by first- year revenues and employee hires, may be evenly scattered across the wealth distribution. As we were primarily concerned with measures of central tendency to compare our results to prior work on liquidity constraints, we removed outstanding outliers from our study. But the outliers are often an important part of the story. The outlier in our sample is one successful nascent entrepreneur who started a new venture employing 200 people, with only a high school diploma and a household net worth of $86,000. The venture is in the field of satellite telecommunication, so it is reasonable to assume this case is not an error. Further research might address these outlier ventures, as well as the high degree of within-sample variation. The heterogeneity that characterizes so many aspects of entrepreneurship likely applies to nascent entrepreneurs no matter where they lie within the wealth distribution (Davidsson 2004).

Our research design addresses limitations in prior studies and makes four key contributions to the literature. First, we use a nationally representative sample of nascent entrepreneurs that more closely captures entry of entrepreneurs into the economy. This contrasts with government datasets measuring self- reported, year-by-year employment status changes (i.e., from wage work to self-employment). When these individuals suddenly appear as ''self-employed,'' they have already overcome the hurdle of disengagement and are likely wealthier, resulting in an upward bias of estimates. Second, we resolve conflicting findings by focusing on startup gestation and wealth percentiles. Some studies have used data acquired during startup gestation without considering wealth relative to its position in the distribution (Kim et al. 2006).

Other studies examine wealth percentiles, but do not capture individuals operating in gestation before a venture is created (Fairlie and Krashinsky 2012). In the current study, we capture entrepreneurial entry much earlier in the process while examining the percentile within the wealth distribution. Third, we employ a methodological strategy that reduces endogeneity bias. We ensure the timing of our wealth measures occur prior to new venture creation. Finally, we take the additional step of examining how wealth affects the early performance of new firms, while controlling for human capital, industry complexity, and a battery of covariates that have been shown to proxy wealth.

One implication for future research based on our findings is the importance of differentiating nascent entrepreneurs who disengage during gestation from those who remain in gestation or start new ventures. In our analysis of the latter, our findings mirror those of Kim et al. (2006) and Hurst and Lusardi (2004) who found wealth to have no effect on startup outcomes. However, when we investigated the entire sample including those who had not yet quit, we found a steep drop in the likelihood of disengagement (Fig. 2) occurring at the 66th percentile, or approximately $300,000 personal net worth. This steepening relationship takes place at a much lower point in the wealth distribution than what was observed by Hurst and Lusardi (2004). They found liquidity constraints occur at the 95th percentile of the wealth distribution. We believe our focus on startup gestation and disengagement explains this difference. Prior work relied on data containing self-reported, year-by-year employment status changes (e.g., from wage work to self-employment). When these individuals suddenly appear in the data as ‘‘self-employed,’’ they have already overcome the hurdle of disengagement and are likely wealthier. This results in an upward bias of estimates. Furthermore, when we dropped the top and bottom 5 % of our sample (by wealth) in our post hoc analysis (thus partially replicating the Hurst and Lusardi study), we expected to find little to no relationship between wealth and entrepreneurship. Yet our results did not change, and we still found that low-wealth and moderately wealthy individuals disengaged at higher rates.

We propose that our focus on disengagement also explains differences between our findings and prior liquidity constraints research also using gestation as the study setting. Kim et al. (2006) and Petrova (2012) both utilized the PSED I and found wealth does not influence startup outcomes. However, when separating disengagement from other outcomes, we find wealth does increase the likelihood of quitting. Interestingly, Kim et al. (2006) found income also did not influence new venture creation. Their inclusion of income as well as personal wealth as predictors was an astute choice because both stock and flow measures of wealth likely impact startup gestation. Income flow can keep a nascent venture alive as it struggles to become an up-and-running new firm. And, nascent entrepreneurs can draw on their stock of wealth to secure loans or convert it into cash. In the present study, we did not include income as a covariate and instead opted to use the amount of personal funds invested. Personal investment during gestation has been shown to be greater when individual net worth is higher (Gartner et al. 2012; de Meza and Southey 1996). These personal investments keep ventures going throughout gestation. To control for this, while maintaining the parsimony of our regression models, we chose a personal investment variable over net income. We found that our flow measure of personal investment did not influence new venture creation or disengagement, echoing prior findings by Kim et al. (2006) and Petrova (2012). However, personal investment did influence the performance of successful new ventures. For every $100,000 invested, new ventures earned 35 % more revenue and hired 24 % more employees than other ventures. Future studies might further investigate the influence of both stock and flow measures of wealth on entrepreneurial outcomes. They might also investigate the link between entrepreneurial self-efficacy, wealth, and startup outcomes. Prior research shows that individuals with high self-efficacy invest a greater proportion of their wealth into their ventures (Cassar and Friedman 2009). Self-efficacy may therefore moderate the relationship between wealth and new venture creation and performance.

Our findings are in line with prior research showing how unemployed individuals entering into self-employment (termed ‘‘non-job-losers’’) are less wealthy while gainfully employed individuals are wealthier (Fairlie and Krashinsky 2012). When controlling for the ‘‘job-loss’’ of these individuals, we find those gainfully employed upon entering startup gestation were 30 % less likely to disengage. However, unlike past research, we show that while unemployed nascent entrepreneurs are more likely to disengage, they are just as likely to start a new venture if the initial hurdle of disengagement is surpassed. The ‘‘job-losers’’ subsample appears to drive disengagement rather than new venture creation. This is an important distinction because there are still low-wealth, middle-class, and wealthy nascent entrepreneurs among the subsample of those who continue in gestation or start new ventures. Our findings regarding new venture performance also extend this vein of research. We demonstrate that individuals gainfully employed upon entering gestation earn 77 % more revenue from their new ventures. Again, we note the power of our tests of performance is limited by the relatively small sample of only a couple hundred successful new ventures. Future research could investigate these questions using larger samples of recently launched new ventures.

Future research could also explore the boundary conditions of liquidity constraints theory. For example, while we control for team effects, we were unable to assess the exact wealth of each member of the startup team. Team composition may also moderate liquidity constraints as each member may bring a diversity of experiences and resources to the venture

(Steffens et al. 2012). Interestingly, we found that teams are 26 % more likely to disengage while twice as likely to start a new venture once surpassing the disengagement hurdle. We interpret this as teams using that experience not only to successfully start new ventures, but also to recognize when an opportunity should be abandoned. Similarly, we found teams earning 2.12 times more revenue and hiring 24 % more employees. We did not, however, account for the additional human capital and networking effects that teams bring to the startup process (although we did account for team size and the number of non-owner helpers). Our reasoning was twofold. First, we aimed to preserve the parsimony of our regression model, which focused on controlling for wealth endogeneity and already included team and human capital predictors. Second (and in the same vein), we felt developing an adequate model examining team effects on wealth and startup outcomes justified a separate research study. The link between teams, wealth, and startup outcomes is an important research opportunity addressing a clear gap in the literature on liquidity constraints theory.

The link between race, wealth, and startup outcomes is another promising area of research. We found African-Americans are 40 % less likely to disengage during gestation, but 60 % less likely to successfully start a new venture, compared to Whites. African-Americans are sticking it out prior to launch, but they are less likely to succeed later. When they do succeed, they hire 2.47 times the number of employees as White-owned ventures (Asians and Hispanics also hire more employees). These results are the same with or without inclusion of personal wealth as a predictor. We interpret this to mean the opportunities minority nascent entrepreneurs pursue during gestation are viable, but other factors intervene to limit their eventual success. Differentiating between stock and flow measures of wealth (i.e., net worth versus net income) could shed light on these findings. Although wealth did not influence these findings in our model, it is conceivable that a lack of income makes it difficult to keep the venture afloat all the way to the end.

The effect of unexpected, external shocks to nascent entrepreneurial activity is another boundary condition to liquidity constraints to be explored. Our post hoc analysis of respondents' primary motivations for abandoning their efforts reveals more than half did so due to money-related problems. When we controlled for covariates that were strongly correlated with liquidity constraints, the motivations most likely to result in disengagement were personal (e.g., health problems, divorce) or the existence of other opportunities (e.g., educational, occupational, or entrepreneurial). This was true across the wealth distribution (although the top tertile was even less likely to report money issues as their motivation, suggesting some support for the liquidity constraints hypothesis still remained even after controlling for those covariates). When we compare the existence of other opportunities to personal reasons as reasons for disengaging, low-wealth and middle-class nascent entrepreneurs overwhelmingly quit for personal reasons compared to the wealthy. This suggests wealth may act as a cushion to protect or otherwise allow nascent entrepreneurs to put their efforts on hold if health or family issues limit their ability to act. Alternatively, given our finding that avoiding disengagement may mitigate the effect of liquidity constraints for low-wealth nascent entrepreneurs, future studies could also examine the extent to which tenacity (Gatewood et al. 2002) or passion (Cardon et al. 2009) drives sustained engagement under liquidity constraints.

One factor that we do not control for in this study is the strength of the housing market. This may partially explain entry and performance based on wealth. Recent research using the Federal Reserve's Survey of Consumer Finances finds that for the wealthiest 1 % of Americans, 9 % of their net worth is in their primary residence compared to 63 % for the middle class (Wolff

2014; Zumbrun 2014). For would-be nascent entrepreneurs whose principal barrier to entry is money, but who have the majority of their net worth tied to their home, the decision to become an entrepreneur will depend on (a) a willingness to assume the risk of taking out a second loan on their home, and (b) the ability to do so (a lender must agree to the transaction). Future research could look into the relationship between the proportion of net worth that is tied up in a home, individual risk profiles, and banks' willingness to loan money on a second mortgage.

Another limitation of this study is that understanding the precise type of opportunity pursued may explain why more nascent entrepreneurs abandon in the lower tertiles. Although we operationalize our industry variable in a manner reflecting the reality that some industries require more wealth to get into (Lofstrom et al. 2014), we do not measure demand or market conditions surrounding the product or service offering. Clearly, demand factor fluctuations can affect whether a new venture is created or abandoned.

6. Conclusion

A high, personal net worth greatly reduces the likelihood of disengaging from the startup process. Once this hurdle is overcome, however, wealth does not appear to affect the successful launch of new ventures. Low-wealth, moderately wealthy, and wealthy nascent entrepreneurs are equally likely to start new ventures, once quitting is avoided. When considering the impact on the larger economy that these new ventures have, in terms of revenues and employees hired, we observe that the founders of these ventures come from across the entire wealth distribution. Low-wealth, middle-class, and wealthy founders appear equally likely to earn money and hire people in numbers both large and small. Taken together, these findings suggest that entrepreneurial talent may be widespread in society, but the opportunity to start a business may be subject to wealth constraints for the low wealth and middle class. This study is the first to examine the impact of wealth on first-year venture performance in a systematic manner that is generalizable to the population of new firms in the USA. Further research is needed, however, to investigate whether this performance relationship is due to the relatively small sample of new firms used in this study.

Understanding the effects of wealth on new firm creation, and on the impact that those new firms have on society, is a question that gets at the heart of what entrepreneurship represents. It can provide upward, socioeconomic mobility to individuals and their families. It can generate employment opportunities in a struggling area. Yet, entrepreneurship's role as a moderator of economic inequality is unclear. The increasing concentration of wealth at the top may, in fact, be amplified by new venture creation if greater wealth increases the odds of success (Piketty 2014). Our study underscores the complexities inherent to studying wealth constraints and entrepreneurial entry and performance, and supports the need for further research into the boundary conditions of extant theory.

Although entrepreneurial success may be concentrated at the top and that entrepreneurialism may therefore be an amplifier rather than modifier of wealth inequality in society (Piketty 2014), our research does not mean we should discourage startup activity. New venture creation still grows the pie—perhaps just not toward a more even distribution. Likewise, we should not claim that our results provide conclusive support that society would be better off if low-wealth entrepreneurs had greater access to capital. We support the idea that entrepreneurship is a ladder toward upward, socioeconomic mobility. What we aim to investigate is who gets on the ladder, who stays on, how much they contribute to society, and the role of wealth throughout the process.

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Table 1 Cronbach Alpha for 5-item scale: COMMUNITY SUPPORT (0.6955)

Item	No. Observations	Sign	Item-test correlation	Item-test correlation	Avg. inter-item covariance	Alpha
AP6	1194	+	0.6938	0.4024	0.4638	0.6811
AP7	1189	+	0.7596	0.5207	0.3856	0.6033
AP8	1181	+	0.7212	0.4776	0.4264	0.6319
AP9	1190	+	0.7338	0.5235	0.4200	0.6079
Test Scale					**0.4240**	**0.6955**

Table 2 Distribution of 2005 Net Worth, General Population versus Nascent Entrepreneurs (confidence intervals in parentheses)

Percentile of General Population Distribution	Net Worth of General Population	Equivalent Net Worth for Nascent Entrepreneurs	Corresponding Percentile for Nascent Entrepreneurs
10th	-$800 (±$272)	-$800	9th (±3.5%)
30th	$14,555 (±$678)	$14,555	20th (±3.5%)
50th	$93,205 (±$1,676)	$93,205	42nd (±3.5%)
70th	$245,188 (±$3,573)	$245,188	63rd (±3.5%)
90th	$678,745 (±$17,374)	$678,745	85th (±3.5%)
		Sample Size	1,112

Table 3 Summary Statistics of New Firms versus Quitting, by Net Worth Tertiles

Net Worth Tertile	**Outcome** Engaged New Firm	In Process Not Yet a New Firm	Disengaged Quit	Ratio: New Firm:Quit	Total
0th – 33rd	71	73	197	0.36	341
33rd – 66th	70	83	198	0.35	351
66th – 100th	105	100	167	0.63	372
Total	246	256	562	0.44	1,064

Table 4 Pairwise Correlations for Key Variables

	1	2	3	4	5	6	7	8	9	10
1. Outcome	1.000									
2. Revenue	--	1.000								
3. Employee	--	--	1.000							
4. Wealth	-0.0038	0.0602	-0.0139	1.000						
5. Team	0.0287	0.1594	0.0481	0.0804	1.000					
6. Helpers	-0.0369	-0.0026	-0.0231	-0.0141	-0.0144	1.000				
7. Personal $	-0.0411	0.3969	0.0175	0.9066	0.0976	-0.0033	1.000			
8. Gainful Emp	-0.1082	0.0669	-0.1225	-0.0614	0.0289	-0.0172	-0.0397	1.000		
9. Business Type	-0.0024	0.0643	0.1505	-0.0163	0.0519	0.0409	0.0147	0.0201	1.000	
10. Industry	0.0249	0.1345	0.1807	-0.0178	0.1090	-0.0129	0.0047	-0.0004	0.0464	1.000
11. Education	-0.0708	0.0836	-0.0428	0.0997	0.0171	0.0154	0.1057	0.0943	0.0779	-0.0873
12. Startup Exp	-0.0527	-0.0287	-0.0354	0.1858	0.0487	0.0174	0.1639	0.0160	0.0724	-0.0172
13. Manager Exp	-0.1345	-0.0168	0.0103	0.1160	0.0587	-0.0340	0.1164	0.0046	0.0656	-0.0096
14. Community	0.0458	0.0329	-0.0411	0.0168	-0.0188	-0.0210	0.0350	0.0597	-0.0103	0.0389
15. Race	-0.0066	-0.0807	0.0202	-0.0318	0.0201	0.0731	-0.0257	-0.0288	0.0005	0.0815
16. Sex	-0.0814	0.1112	0.0544	0.0284	0.0920	0.0001	0.0606	0.0922	-0.0213	0.0822
17. Time	-0.1388	0.0105	-0.0558	0.0179	-0.0511	0.0299	0.0367	0.0133	-0.0372	0.0204

	11	12	13	14	15	16	17
12. Startup Exp	0.1468	1.000					
13. Manager Exp	0.2595	0.3302	1.000				
14. Community	0.0013	0.0812	-0.0341	1.000			
15. Race	-0.1354	-0.0531	-0.1833	0.0719	1.000		
16. Sex	-0.0533	0.0381	0.0617	0.0692	0.0258	1.000	
17. Time	0.0203	-0.0011	0.0748	0.0398	-0.0009	0.0598	1.000

Table 5 Cox Regression for Nascent Entrepreneurs' Risk of Disengaging as a Function of Wealth (Hypothesis 1a)

Variable	Model 1 Covariates only		Model 2 Wealth variable included	
	β	exp(β)	β	exp(β)
Team	0.2328* (0.1017)	1.2621	0.2650** (0.1018)	1.3035
Non-owner helpers	-0.0354 (0.0249)	0.9653	-0.0404 (0.0250)	0.9604
Personal funds invested	-0.0559 (0.0518)	0.9457	-0.0480 (0.0470)	0.9531
Gainfully employed at decision to start	-0.0345*** (0.0961)	0.7083	-0.0334*** (0.0965)	0.7157
Business type (takeover)	0.2629 (0.2536)	1.3006	0.2995 (0.2541)	1.3492
(franchise)	0.5726** (0.2083)	1.7728	0.5078* (0.2097)	1.6617
(multilevel mktng)	0.6108*** (0.1852)	1.8420	0.5994** (0.1851)	1.8210
(firm sponsored)	0.0877 (0.1908)	1.0916	0.0923 (0.1910)	1.0967
Industry complexity	0.0069 (0.1012)	1.0069	0.0414 (0.1019)	1.0423
Education (< high school)	0.0168 (0.2177)	1.0169	0.0342 (0.2184)	1.0348
(high school)	0.0169 (0.2087)	1.0170	0.0416 (0.2094)	1.0424
(some college)	0.1560 (0.2159)	1.1688	0.2343 (0.2183)	1.2641
(Bachelors)	-0.0889 (0.2403)	0.9149	0.0206 (0.2426)	1.0208
Startup experience	-0.0260 (0.0314)	0.9744	-0.0137 (0.0312)	0.9864
Managerial experience	-0.0206*** (0.0059)	0.9796	-0.0180** (0.0060)	0.9821
Community support	0.0987† (0.0545)	1.1037	0.0914† (0.0544)	1.0957
Race (African American)	-0.5338*** (0.1172)	0.5863	-0.5832*** (0.1186)	0.5581
(Asian/Hispanic)	0.2691 (0.1305)	1.0273	0.0245 (0.1302)	1.0248
Sex	-0.1208 (0.0949)	0.8862	-0.1153 (0.0944)	0.8911
Wealth Tertile 1 (0 – 33)			0.3779** (0.1168)	1.4592
Tertile 2 (33 – 66)			0.2459* (0.1132)	1.2788
Sample Size	1025		1025	
Δ X^2 (df)	5.95** (df = 1)		10.88*** (df = 1)	
R^2	0.08		0.09	

† $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

Table 6 Logistic Regression for Nascent Entrepreneurs' Probability of Starting a New Firm as a Function of Wealth, Given They Did Not Disengage from the Process (Hypothesis 1b)

Variable	Model 3 Covariates only		Model 4 Wealth variable included	
	β	exp(β)	β	exp(β)
Intercept	1.045 (0.7681)	2.8434	0.8261 (0.8038)	2.2844
Team	0.6454* (0.2691)	1.9067	0.6838* (0.2733)	1.9814
Non-owner helpers	0.0547 (0.0472)	1.0562	0.0526 (0.0479)	1.0540
Personal funds invested	-0.0043 (9.5620)	0.9957	-0.4396 (0.9.415)	0.6443
Gainfully employed at decision to start	-0.2251 (0.2830)	0.7984	-0.2072 (0.0284)	0.8129
Business type (takeover)	0.2405 (0.5678)	1.2719	0.2460 (0.5693)	1.2789
(franchise)	1.1120 (0.7073)	3.0404	1.0460 (0.7067)	2.8462
(multilevel mktng)	0.0563 (0.5686)	1.0579	0.0684 (0.5684)	1.0708
(firm sponsored)	0.0464 (0.0415)	1.0475	0.4317 (0.4181)	1.5399
Industry complexity	-0.1174 (0.2666)	0.8892	-0.0922 (0.2687)	0.9119
Education (< high school)	0.4622 (0.6005)	1.5876	0.4785 (0.5984)	1.6137
(high school)	0.3774 (0.5707)	1.4585	0.4015 (0.5693)	1.4941
(some college)	0.4243 (0.6065)	1.5285	0.4864 (0.6078)	1.6265
(Bachelors)	0.4812 (0.6201)	1.6180	0.5777 (0.6274)	1.7819
Startup experience	-0.0425 (0.0645)	0.9584	-0.0376 (0.0646)	0.9631
Managerial experience	-0.0005 (0.0132)	0.9995	0.0017 (0.0135)	1.0017
Community support	0.1048 (0.1531)	1.0149	0.1028 (0.1530)	1.1083
Race (African American)	-0.9108** (0.2840)	0.4022	-0.9357** (0.2863)	0.3923
(Asian/Hispanic)	0.2912 (0.3752)	1.3380	0.3059 (0.3759)	1.3578
Sex	-0.4204† (0.2401)	0.6568	-0.4288† (0.2407)	0.6513
Time	-0.0242*** (0.0031)	0.9761	-0.0241*** (0.0031)	0.9762
Wealth Tertile 1 (0 – 33)			0.2587 (0.3011)	1.2952
Tertile 2 (33 – 66)			0.1717 (0.2828)	1.1873
Sample Size	508		494	
ΔX^2 (df)	2.37 (df = 1)		1.42 (df = 1)	
McFadden Pseudo R^2	0.2154		0.2166	

† $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

Table 7 OLS and Poisson Regressions (Hypotheses 2a and 2b) for First-Year Revenue and Employee Hires as a Function of Wealth, Given Successful New Firm Creation

Variable	Model 5a Revenue	Model 5b	Model 6a Employees	Model 6b
	β	β	β	β
Intercept	0.1037*** (0.8281)	0.1039*** (0.8376)	0.2804 (0.3747)	0.2744 (0.3784)
Team	0.7801*** (0.2208)	0.7703*** (0.2246)	1.1190*** (0.1090)	1.1210*** (0.1109)
Non-owner helpers	0.0002 (0.0215)	0.0011 (0.0219)	-0.0188 (0.0159)	-0.0191 (0.0162)
Personal funds invested	0.4958*** (0.1006)	0.4932*** (0.1016)	0.0893** (0.0331)	0.0897** (0.0334)
Gainfully employed at decision to start	0.6496** (0.2447)	0.6544** (0.2476)	-0.1808 (0.1275)	-0.1830 (0.1294)
Business type (takeover)	1.3230** (0.4578)	1.3240** (0.4603)	0.2451 (0.2302)	0.2456 (0.2304)
(franchise)	0.9765* (0.4551)	0.9835* (0.4580)	1.2760*** (0.1781)	1.2740*** (0.1787)
(multilevel mktng)	0.7348 (0.5667)	0.7413 (0.5698)	0.6353† (0.3260)	0.6325† (0.3272)
(firm sponsored)	0.6230† (0.3163)	0.6315* (0.3202)	0.6548*** (0.1379)	0.6522*** (0.1404)
Industry complexity	0.2641 (0.2318)	0.2608 (0.2351)	0.5942*** (0.1054)	0.5950*** (0.1087)
Education (< high school)	-0.2017 (0.7137)	-0.1743 (0.7237)	-0.4331 (0.3158)	-0.4396 (0.3219)
(high school)	-0.8364 (0.6852)	-0.8103 (0.6955)	0.0503 (0.2864)	0.0426 (0.2945)
(some college)	0.2597 (0.7076)	0.2727 (0.7144)	0.2338 (0.2986)	0.2306 (0.2997)
(Bachelors)	-0.5807 (0.7183)	-0.5725 (0.7232)	-0.3218 (0.3118)	-0.3255 (0.3138)
Startup experience	0.0460 (0.0589)	0.0425 (0.0606)	-0.0327 (0.0368)	-0.0314 (0.0384)
Managerial experience	0.0074 (0.0110)	0.0069 (0.0112)	0.0038 (0.0056)	0.0038 (0.0569)
Community support	-0.1169 (0.1284)	-0.1160 (0.1295)	-0.2460*** (0.0600)	-0.2448*** (0.0610)
Race (African American)	-0.6595* (0.2898)	-0.6504* (0.2952)	0.7302*** (0.1352)	0.7264*** (0.1441)
(Asian/Hispanic)	-0.6784* (0.2991)	-0.6810* (0.3008)	0.7126*** (0.1382)	0.7127*** (0.1383)
Sex	0.0674 (0.2018)	0.0664 (0.2044)	0.1090 (0.1101)	0.1099 (0.1107)
Time	-0.0010 (0.0020)	-0.0010 (0.0020)	0.0018† (0.0010)	0.0018† (0.0010)
Wealth Tertile 1 (0 – 33)		-0.0671 (0.2601)		0.0169 (0.1414)
Tertile 2 (33 – 66)		-0.0556 (0.2515)		0.0110 (0.1375)
Sample Size	245	218	250	243
F value	7.037*** (df = 210)	6.342*** (df = 208)		
Δ X^2 (df)	0.02 (df = 1)	0.09 (df = 1)	1.62 (df = 1)	0.01 (df = 1)
R^2	0.3443	0.3382	0.367	0.367

† $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

Figures

Figure 1 Percentile Distribution of Net Worth of General Population (Dots) & Nascent Entrepreneurs (Dashed Line with Shaded 95% Conf. Interval)

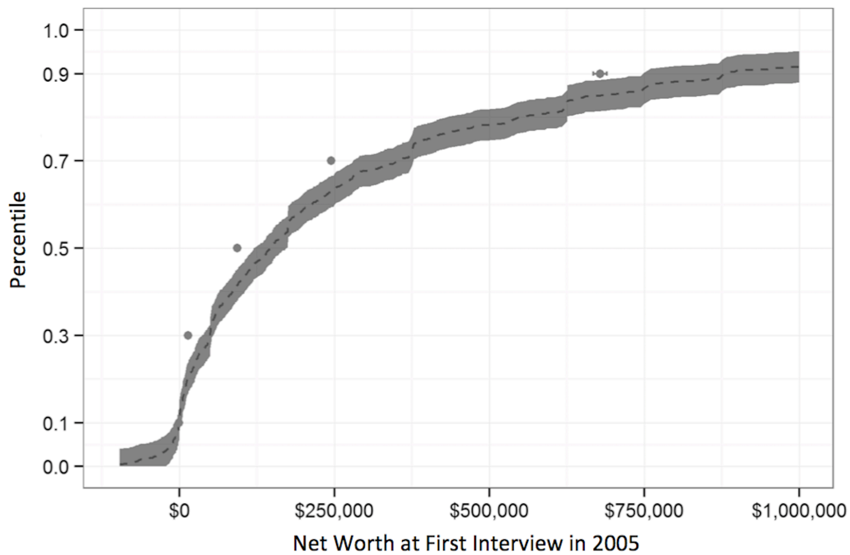

Figure 2 Probability of Quitting the Startup Process as a Function of Wealth

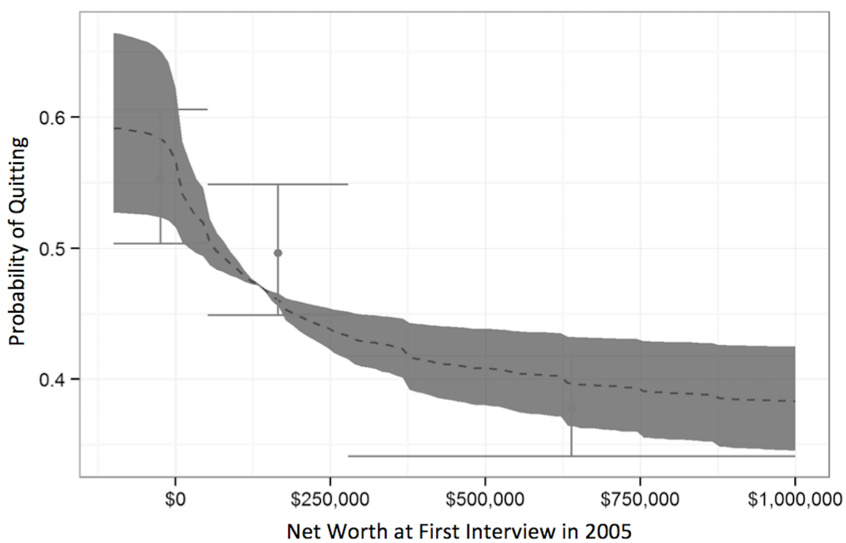

Figure 3 Probability of Starting a New Firm (Given Not Having Quit) as a Function of Wealth

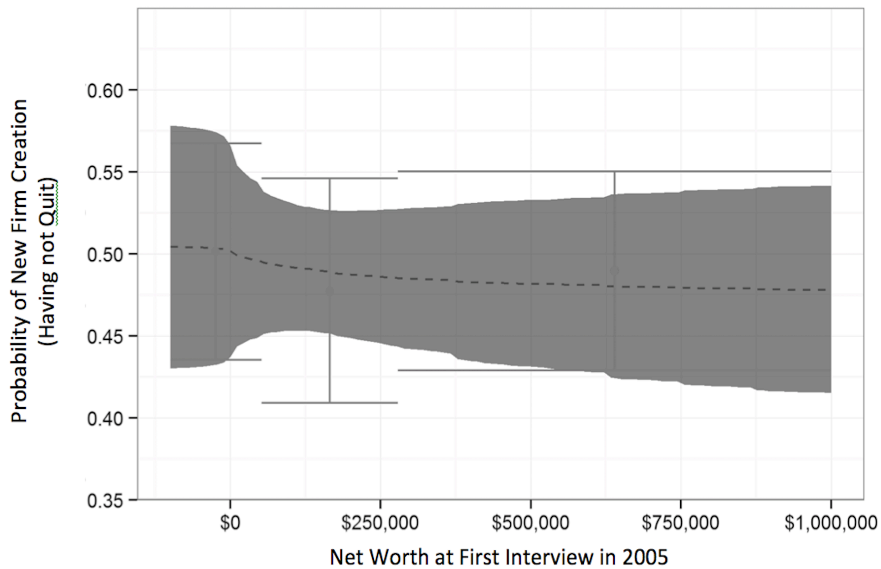

Figure 4 New Firm, Year 1 Revenues as a Function of Founder Wealth

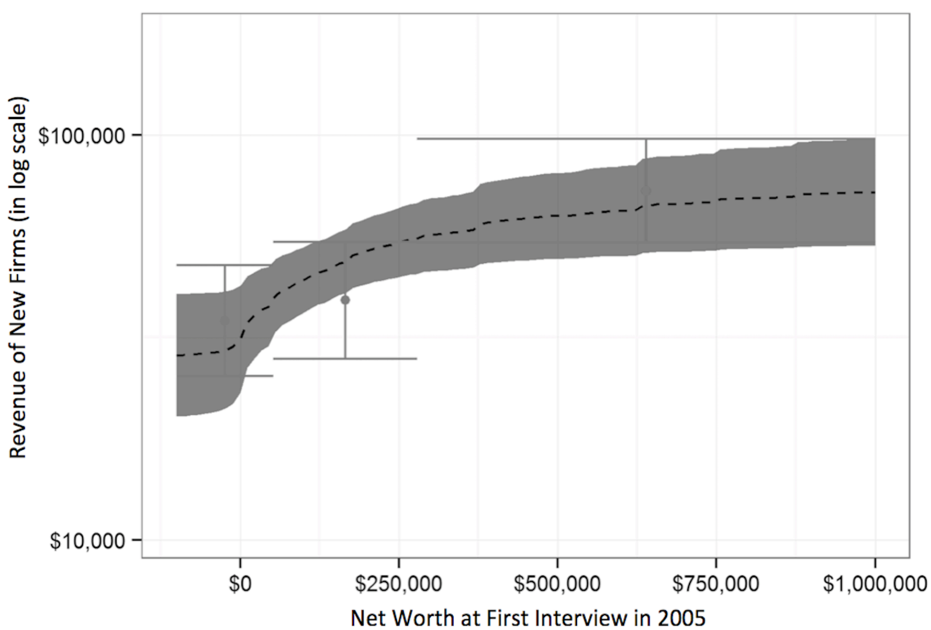

Figure 5 New Firm, Year 1 Employee Hires as a Function of Founder Wealth