ESSAYS ON SELF-EMPLOYMENT OF YOUNG WORKERS

DISSERTATION

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By

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ABSTRACT

Academic interest in self-employment has grown rapidly in recent decades. However, relatively little is known about the longitudinal patterns of young self-employed workers. In the first essay, I examine the patterns of self-employment that appear in the 1979 National Longitudinal Survey of Youth (NLSY79). I find that most of self-employed workers hold wage jobs before entering self-employment and come back to wage sector after experiencing one or two self-employment spells. Self-employment jobs differ in terms of industry distribution, for both men and women and they are—female self-employment jobs, in particular—likely to entail changes in industry. Additionally, I find that female self-employment spells are more likely to be followed by a large percent of time nonemployed and a small percent of time in the same industry compared to the wage employment while the opposite are true for the male self-employment spells.

Risk tolerance and liquidity constraints are widely believed to be key determinants of self-employment, but their independent effects have proved difficult to identify. In the second essay, I specify a theoretical model that illustrates how individual risk tolerance and liquidity constraints affect the decision to become self-employed. I then tackle the empirical identification problem by constructing a measure of risk tolerance that is corrected for reporting error, varies with age and assets, and allows for the endogeneity of

assets. In contrast to previous studies that use regional variation in housing prices as an instrument for assets, I address the fact that housing appreciation affects homeowners and nonowners differently. I find that risk tolerant workers are more likely to be self-employed than are their less risk tolerant counterparts. However, net asset levels have an insignificant effect on self-employment entry once absolute risk tolerance is properly taken into account.

The absence of successful businesses owned by minorities, and by blacks in particular, is a concern for policy makers. In the third essay, I exploit detailed work history data in the NLSY79 to provide new evidence on the reasons behind the race gap in self-employment. My analysis of an "age uniform" sample of men, all of whom are observed from age 22 to age 40, reveals that racial differences in cross-sectional self-employment rates are largely due to the fact that minority workers' self-employment spells are relatively short-lived. Moreover, I find that minority workers' relatively high exit rates from self-employment are caused primarily by transitions to nonemployment. Estimates from a multinomial logit model of self-employment exits suggest that minority workers' weak attachment to the labor market prior to entering self-employment is an important determinant of their self-employment to nonemployment transitions, while lack of prior industry and self-employment experience contributes to minorities' transitions to nonself-employment.

Dedicated to my parents and my family

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CHAPTER 1

INTRODUCTION

Self-employment has become a major interest for economists and policy makers in recent decades. Researchers have sought to understand what drives people to enter self-employment, which workers are self-employed, and how self-employment differs from traditional employment. Answers to these questions will enable us to understand not only the behavior of the self-employed but also the effects of self-employment on individual and social welfare.

A large portion of research on self-employment examines the determinants of self-employment and entrepreneurship. Liquidity and assets are most frequently cited as the key determinants of self-employment. Several studies investigate the effects of liquidity constraints on self-employment probabilities (Evans and Jovanovic 1989; Blanchflower and Oswald 1998; Dunn and Holtz-Eakin 2000). Besides financial resources, some researchers argue that the transmission of entrepreneurial skill across generation and within household increases the probability of self-employment (Dunn and Holtz-Eakin 2000; Bruce 1998).

Risk taking attitude is regarded to be a key characteristic of entrepreneurs but relatively few papers empirically investigate whether risk attitude affects self-employment decisions (Cramer, Hartog, and Van Praag, 2002; Farlie 2002). Non-pecuniary benefits from self-employment are also among the factors believed to

encourage self-employment. Hamilton (2000) finds that earnings growth among self-employed workers are lower than those of alternative wage workers despite high volatility of self-employment earnings. This finding suggests that a taste for independence or autonomy is an important determinant of self-employment. Some studies suggest that poor wages, unfavorable working conditions, unstable job security, and increasing inequality between skill levels push low wage workers into self-employment (Evan and Leighton 1989; Borjas 1999). Similarly, some researchers argue that female self-employment is a response to discrimination in the workplace (Budig 2004) or a balancing of household work and wage work (Hundley 2000; Taniguchi 2002).

It is well documented that the self-employment rate of minority workers is significantly lower than that of white workers. According to statistics from the 2003 Current Population Survey (CPS), 14.5% of white male workers are self-employed, versus only 7.5% of blacks and 8.4% of Hispanics (Hipple 2004). The relative lack of businesses owned by minorities, and by blacks in particular, is a concern for policy makers and researchers. Prior research that seeks to identify determinants of racial and ethnic differences in self-employment has shown that relatively low rates of parental self-employment, low levels of wealth, and low schooling levels are important contributors to the low self-employment rates of black workers (Fairlie 1999, 2006; Hout and Rosen 2000; Lofstrom and Wang 2006).

In my dissertation, I contribute to this literature on self-employment by conducting an empirical investigation on self-employment of young workers using data from the 1979 National Longitudinal Survey of Youth (NLSY79). In the first essay, I describe various patterns that emerge in data from an "age uniform" sample of men and

women, all of whom are observed from age 22 to age 40. In the second essay, I investigate the roles of risk tolerance and liquidity constraints in self-employment entry decisions recognizing the fact that risk preference and personal assets are interrelated. In estimating a model of self-employment decision, I construct data on personal net assets for each year and a measure of individual absolute risk tolerance that is corrected for reporting error and that varies with age and assets. In the third essay, I investigate the reasons behind the race gap in self-employment rate using detailed work history of black, white, and Hispanic men. I estimate a multinomial logit model of self-employment exits including various labor market experiences prior to entering self-employment.

CHAPTER 2

SELF-EMPLOYMENT OF YOUNG WORKERS

2.1 Introduction

Academic interest in self-employment has grown rapidly in recent decades. However, relatively little is known about the longitudinal patterns of young self-employed workers. Most research on self-employment focuses on "point in time" entry into self-employment, often using cross-sectional data but considerably less is known about the timing of entry into self-employment, transitions back to wage employment, and the number and the length of unique self-employment spells experienced over the life cycle. It is important to know how self-employment fits into workers' careers as well as how self-employment differs from wage employment because more than a quarter of workers experience self-employment (Ferber and Waldfogel 1998).

In this paper, I briefly describe the patterns of self-employment that appear in the 1979 National Longitudinal Survey of Youth (NLSY79) using an "age uniform" sample of men and women, all of whom are observed from age 22 to age 40. The NLSY79 is a good source for investigating patterns of self-employment from early to mid-careers of workers because it allows us to construct a complete work history for each individual, containing a record of start and end dates of each job held. It also provides detailed information on characteristics of jobs including class of worker, industry, and hourly rate of pay. In addition, it contains detailed demographic characteristics of respondents. Using

these unusually detailed data on work histories and individual characteristics, I investigate the patterns of self-employment during 19 years of the careers of young workers, starting at age 22.

I find that a large portion of self-employed workers hold wage jobs before entering self-employment, hold one or two self-employment spells and come back to wage sector later. Self-employment jobs differ in terms of industry distribution, for both men and women and they are—female self-employment jobs, in particular—more likely to entail changes in industry. Additionally, I find that female workers start self-employment jobs after experiencing a large percent of time nonemployed and not having experience in the same type of business while the opposite hold for male self-employed workers.

2.2 Data

The NLSY79 began in 1979 with a nationally representative sample of 12,686 individuals between ages 14 and 22. Interviews were conducted annually from 1979 to 1994 and biennially thereafter. The original sample consists of three subsamples: 6,111 individuals representing the civilian population born between 1957 and 1964, a supplemental sample of 5,295 black, Hispanic and economically disadvantaged non-Hispanic, non-black youth, and a sample of 1,280 individuals who enlisted in the military as of September 1978.[1] I use data from survey years 1979 to 2004 for my analysis.

I select an "age uniform" sample for my analysis as follows. I use age 22 to initialize my sample because all respondents are at least 22 years old when first

[1] I refer to nonblack, non-Hispanic respondents as whites.

interviewed in 1979. I choose age 40 as my cutoff because relatively few respondents are observed beyond age 40 due to sample attrition. In constructing this age uniform sample, I drop 2,300 men and 1,991 women who left the survey before reaching age 40. I additionally eliminate 67 men and 163 women who did not report any job lasting at least 16 weeks on which he worked at least 30 hours per week. I impose this selection rule in order to exclude the respondents who do not fully participate in the labor market at least sometime during their early life time. The final sample includes 8,165 respondents (4,036 men and 4,129 women); 3,312 (51%) are white, 2,467 (30%) are black, and 1,555 (19%) are Hispanic.

Self-employed workers are defined as those individuals working for profit or fees in their own business, shop, office, or farm; such workers are identified from answers to "class of worker" questions asked in every survey round. Individuals who are working without pay in a family business or farm are not considered to be self-employed. Class of worker information is available for up to five jobs that respondents report each year. In some jobs, class of work information is missing because the question was not asked for jobs on which workers "usually" work less than ten hours a week and jobs held less than nine weeks since the last interview. For other jobs, respondents were asked to report their "class of worker" but valid information was not obtained. In these cases, I impute missing data on self-employment using information from other years if the respondent reported "class of worker" information for the same job in an adjacent interview.[2]

[2] Class of worker information is missing for 12% (7,711) of the 64,258 jobs reported by my 8,165 sample members between ages 22 and 40. I am able to impute self-employment status for 1,194 of those missing cases; the remaining 6,517 jobs are dropped from the sample.

2.3. Empirical patterns of self-employment

2.3.1 Ever self-employed

In Table 2.1, I present the percent of sample members who are ever self-employed between ages 22 and 40. In all, 29% of the 8,165 workers in the sample experience self-employment by age 40. Men are more likely than women to experience self-employment: Table 2.1 shows that 33.1% of men and 25.1% of women are "ever" self-employed during the observation period. For both men and women, blacks are less likely to experience self-employment than Hispanics and whites. Table 2.1 reveals that 28.7% of black men and 17.2% of black women experience self-employment, while 36.5% of white men and 29.9% of white women do so; Hispanics are intermediate to blacks and whites in their self-employment rates.

The self-employment rates seen in Table 2.1 are larger than what is seen in cross-sectional data used by other researchers. Using data from the 2003 Current Population Surveys (CPS), Hipple (2004) finds that the self-employment rate is 3% for employed men ages 20 to 24, 8.4% for employed men ages 25 to 34 and 14.3% for employed men ages 35 to 44. For employed women, the corresponding self-employment rates are 1.7%, 5.8% and 9.0%. The large difference in self-employment rates between Hipple's cross-sectional sample and my longitudinal sample may reflect the fact that self-employment is often short-lived, and therefore unseen at a given point in time. In order to explore the longitudinal pattern of self-employment in more detail, I investigate when workers first enter self-employment, how many unique self-employment jobs they hold and how long they are self-employed in the next subsection.

2.3.2 Timing and duration of self-employment

In Table 2.2 and 2.3, I summarize when "ever-self-employed" workers first enter self-employment. Table 2.2 shows the distribution of the ages at which workers in my sample first enter self-employment. Men enter self-employment earlier than women by one year: the mean starting age of self-employment is 28.7 for men and 29.9 for women. Among men, 30.9% of those who experience self-employment by age 40 begin their first self-employment job by age 25. In addition, more than 67.2% of men start their first self-employment by age 30. For women, the corresponding figure is 60.1% and ages of first self-employment are distributed fairly uniformly over the first 9-year window.

I ask how many workers stay in self-employment sector until the end of observation window. Table 2.2 suggests that a considerable fraction of workers who enter self-employment does not stay in self-employment sector but returns to the wage sector. While only 29.5% of "ever-self-employed" workers are self-employed at age 40, women are less likely to stay self-employed than men are; 25.6% of women are self-employed at age 40 while 32.4% of women are self-employed at age 40. Men whose entries are in the earliest age range (*i.e.* 22 to 25) are more likely to stay in self-employment until age 40 compared to the other men who enter self-employment before age 34. But in general, for both men and women, those who enter self-employment at later ages are more likely to be self-employed at age 40 than those who enter at earlier ages as expected. I explore the pattern of self-employment spells in more detail in subsequent tables

Table 2.3 describes the number of jobs held before first self-employment. Most of the workers enter self-employment after holding a few wage jobs. Only 13.3% of men and 11.8% of women hold no job before they are first self-employed. At the other

extreme, about 11.1% of men and 10.6% of women hold nine or more wage jobs before entering self-employment for the first time. As we also saw in Table 2.3, there is no dominant pattern regarding the timing of first self-employment job. On average, men and women hold four jobs before they are first self-employed.

I summarize the number of self-employment spells held by "ever self-employed" workers in Table 2.4. More than 85% of "ever self-employed" respondents have no more than two self-employment jobs. While men and women look virtually identical in this dimension, women who enter self-employment are slightly more likely to hold only one self-employment job and less likely to hold three such jobs than male counterparts by 3 percentage points. Table 2.4 may seem to suggest that women hold more stable self-employment jobs than men. However, this is not supported by subsequent analysis on the duration of self-employment jobs.

In Table 2.5, I examine how long the self-employment spells held by "ever self-employed" workers last during the 19-years of window. The average duration of self-employment jobs held by male worker is 45 months and this is ten months longer than the duration of female self-employment jobs.[3] However, a significant number of self-employed jobs held by each gender group are quite short: 30.1% of men's and 33.3% of women's self-employment jobs last less than a year. The information on number and duration of self-employment jobs reported in Table 2.4 and 2.5 suggests that self-employment is not a long-lasting state for workers in the early career. While close to a third of young workers ever enter self-employment, a majority of them just holds one or

[3] For jobs that start before age 22, actual starting date is used. For jobs that end before the last interview, true duration is used. If the job is right-censored, the last interview date is used as the ending date.

two self-employment jobs that last only two or three years each. In light of the transitory nature of self-employment, it is unsurprising that cross-sectional surveys would show much less self-employment rate than the "ever self-employment rate" found in the NLSY79.

2.3.3 Industry distribution of self-employment jobs

In the previous subsection, I learn that most of "ever-self employed' workers hold wage jobs before entering self-employment. In Table 2.6, I summarize the distribution of industry of self-employment jobs and the preceding wage job prior to holding those self-employment jobs.[4] The largest share (27%) of male self-employment jobs is in construction industry. The next frequent industry categories are repair service (10.6%), agriculture (9.9%), and retail/wholesale trade (9.8%). While a largest share of preceding wage jobs is in construction (19.1%), more than 10% of preceding jobs are in manufacturing industry. In addition, repair service industry accounts for only 4.8% of previous wage jobs while it is the second most frequent industry among self-employment jobs.

Table 2.6 also reveals substantial difference in the industry distribution between self-employment jobs and preceding wage jobs for female workers. Female self-employed workers are highly concentrated in personal service (27.5%) and private household service (20.8%). While personal service industry accounts for the largest portion (17%) of the preceding wage jobs, the percent is 10.5 percentage point lower than

[4] From the survey year 2002, the industry and occupation classification codes used in the NLSY79 have changed. I only present the distribution of industries because the changes in occupation code are too substantial to make a consistent occupation classification across year even in one-digit level.

self-employment jobs. Another prominent difference between self-employment jobs and preceding wage jobs is shown in the share of private household industry—only 7.3% of preceding wage jobs is in private household. The fact that private household and personal service accounts for almost a half of female self-employment jobs but that the two industries account for only 24.3% of preceding wage jobs may suggest that housework and childrearing are important determinants of female self-employment (Budig 2004; Hundley 2000; Taniguchi 2002).

2.3.4 Industry change, employment status and duration of self-employment

The preceding table suggests that there are substantial changes in industry when workers enter self-employment. In this subsection, I examine the rate of industry changes and the rate of nonemployment before holding self-employment jobs and their relationships with the duration of self-employment spells. Table 2.7 presents the frequency of industry changes of self-employment jobs. In order to identify industry changes, I have to exclude 300 self-employment jobs that are the first jobs held by "ever self-employed" workers during 19-year window from 3,668 self-employment jobs. Additionally, I exclude 82 self-employment jobs that have no industry information, and exclude 40 self-employment jobs if the industries of their preceding wage jobs cannot be identified. Table 2.7 reveals that a large percent of self-employment jobs entail substantial industry changes. While a majority of workers change industry when they enter self-employment for both men (65.5%) and women (73.9%), the rate is higher for women than for men by 8.4 percentage points. The second row of the table suggests that the duration of self-employment job is negatively related to the industry change. For both

men and women, the self-employment jobs which entail industry changes tend to last shorter by 12 months than the jobs without industry change.

Table 2.8 shows how many are nonemployed before holding self-employment jobs. I consider the worker to be nonemployed if he/she hold no job for one month or more before holding a self-employment job. The rate of nonemployment shows considerable gender difference; only 36.6% of self-employment jobs held by male workers are started from nonemployment while 59.6% of female self-employment jobs are started from nonemployment. Nonemployment prior to self-employment is negatively related to the duration of self-employment jobs; the duration of self-employment jobs started from nonemployment is shorter than that of the others by more than ten months for both men and women. Besides, previous employment status is related to industry change of self-employment. Nonemployment increases the rate of industry change by 5.6 percentage points for men 1.5 percent points for women.

The findings in this subsection show that industry change and previous nonemployment are negatively related to the duration of self-employment. In addition, they suggest that relatively short durations of female self-employment jobs is related to the fact that the larger percent of female workers experience nonemployment and change industries when they enter self-employment than male workers.

2.4 Comparison of self-employment jobs and wage jobs

In this section, I compare self-employment jobs and wage jobs spells held by 8,165 respondents in my sample between ages 22 and 40. I consider each job spell to be unique employer-employee or self-employment spell and I take each job spell as one

observation. Total number of observations is 57,741: 30,081 jobs held by 4,036 male workers and 27,660 jobs held by 4,129 female workers. Among 30,081 male jobs, self-employment jobs account for 7.0% (2,113). Among 27,660 female jobs, the corresponding figure is 5.6% (1,555).

Table 2.9 describes current job characteristics, previous labor market experiences, and personal characteristics of male and female job spells by type of employment: wage employment and self-employment. Average hourly earnings of self-employment jobs is higher than that of wage jobs for both men and women. However, median earnings for female self-employment jobs is slightly lower than the wage counterpart. In addition, the standard deviations of self-employment earnings are larger than the standard deviations of wage earnings for both men and women. This may suggest that there exists large heterogeneity among self-employment jobs or that self-employment job are sensitive to economic fluctuation and face more earnings risk relative to wage jobs (Carrington et al 1996). The average duration of self-employment jobs is longer for both men and women but the average difference is much larger for men then for women—14.8 months compared to 4.6 months. The rate incorporated is higher for male self-employment jobs (0.11) compared to the female counterparts (0.08).

To explore the differences in self-employment jobs and wage jobs in more detail, I compare the distribution of industries. While construction industry accounts for the largest share (0.27) of self-employment jobs, the jobs in manufacturing industries account for the largest share (0.17) of male wage employment. Female wage jobs are concentrated in retail/wholesale trade, personal service and health service industries while female self-employed jobs are highly concentrated in personal service and private

household service industry. For both men and women, the industry distribution of wage jobs is similar to that of industry distribution of the wage jobs held prior to self-employment jobs shown in Table 2.6. This similarity in industry distribution suggests that those who become self-employed were not substantially different from the other workers in this dimension.

I investigate the differences in labor experience before the job spells begin. The first two measures present previous labor market experience—the percent of time spent in nonemployment, and the percent of time spent in the same industry as the current job. All two measures are constructed from the individual's 22nd birthday to the start of the current self-employment spell. Additionally, I include age at the start of the spell. Average starting age of self-employment jobs shows that starting ages of self-employment jobs are higher than that of wage jobs for both genders. However, previous work histories show substantial gender differences. Male workers spend less time nonemployed (23.6%) and more time working in the same industry (24.2%) before the start of current self-employment than before the start of the wage employment spells—the percent of time nonemployed (27.5%) and the percent of time in the same industry (21.8%). However, female self-employment spells start after experiencing high percent of time in nonemployment (40.3%) and low percent of time working in the same industry (13.3%) compared to wage employment spells—the percent of time nonemployed (35.5%) and the percent of time in the same industry (18.6%). The findings from previous work histories suggest that self-employed men relatively spend a large share of time in market and in the same industry before they enter self-employment but are the opposite for female self-employed workers.

In the rest if the Table 2.9, I summarize the personal characteristics at the start of the employment spells. Average highest grade completed shows no substantial difference between self-employment spells and wage employment spells for men and women. However, marriage rate and rate of having children at the beginning of the job spell are much higher than those rates at the start of wage jobs for women—by 0.19 and 0.16 respectively. For men, the corresponding differences between self-employment and wage employment are just a half—0.09 and 0.08. The findings regarding previous market experience and personal characteristics may suggest that women are likely to be married, spend more time in housework raising children prior to holding self-employment jobs.

2.5 Concluding remarks

Over a quarter of workers experience self-employment in their early careers. However, we know little about when they are self-employed, how long they remain self-employed, and how self-employment jobs are different from self-employment. Although more substantive analyses should be added, from this brief descriptive study, I find that self-employment is not a long-lasting state for a large portion of ever self-employed workers; they hold a few wage jobs before entering self-employment sector, mostly have one or two self-employment spells, and come back to wage sector. In addition, self-employment jobs, female jobs in particular are more likely to start from nonemployment, entail changes in industry and tend to last short if the industry change occurs.

I find that wage jobs and self-employment jobs differ in terms of industry distribution, for both men and women. Construction industry accounts for the largest share of male self-employment while manufacturing industry does in the male wage

sector. Female self-employment jobs are highly concentrated in personal service and private household service industry while the wage works are mostly likely to be in retail/wholesale trade.

The results in this paper reveal that female self-employment spells are more likely to begin after a large percent of time nonemployed and not in related business compared to the wage employment. However, I find that this is the opposite for male self-employment jobs. Since previous labor market experiences before holding self-employment jobs are different by gender and a number of self-employment are in the middle of workers career, the careful investigation regarding the role of self-employment spells in the workers career path separately for men and women will be an interesting subject for a future study.

	Hispanic	Black	White	All
Men				
Percent who are ever self-employed (ages 22-40)	30.9	28.7	36.5	33.1
[Sample size]	[777]	[1,214]	[2,045]	[4,036]
Women				
Percent who are ever self-employed (ages 22-40)	24.8	17.2	29.9	25.1
[Sample size]	[778]	[1,253]	[2,098]	[4,129]
All				
Percent who are ever self-employed (ages 22-40)	27.8	22.8	33.2	29.0
[Sample size]	[1,555]	[2,467]	[4,143]	[8,165]

Table 2.1: Percent of workers who are ever self-employed between ages 22 and 40

	Men			Women			All		
Age	Number	Percent	SE at 40 (Percent)	Number	Percent	SE at 40 (Percent)	Number	Percent	SE at 40 (Percent)
Less than 25	412	30.9	28.4	215	20.8	12.6	627	26.5	23.0
25-27	263	19.7	22.8	204	19.7	17.2	467	19.7	20.3
28-30	222	16.6	23.0	203	19.6	15.8	425	17.9	19.5
31-33	173	13.0	25.4	152	14.7	20.4	325	13.7	23.1
34-36	99	7.4	43.4	121	11.7	30.6	220	9.3	36.4
37+	166	12.4	71.1	140	13.5	73.6	306	12.9	72.2
All	1,335	100.0	32.4	1,035	100.0	25.6	2,370	100.0	29.5
Mean	28.7			29.9			29.2		
Std. Dev.	5.8			5.3			5.6		

Table 2.2: Distribution of age of first entry into self-employment and percent who stay self-employed at age 40

	Men		Women		All	
No. jobs per person	Number	Percent	Number	Percent	Number	Percent
0	178	13.3	122	11.8	300	12.7
1-2	408	30.6	318	30.7	726	30.6
3-4	281	21.1	235	22.7	516	21.8
5-6	205	15.4	153	14.8	358	15.1
7-8	115	8.6	97	9.4	212	9.0
9+	148	11.1	110	10.6	258	10.9
All	1335	100.0	1035	100.0	2,370	100.0
Mean	3.9		3.9		3.9	
Std. Dev.	3.6		3.4		3.5	

Table 2.3: Distribution of number of jobs held prior to first self-employment

	Men		Women		All	
No. of jobs per person	Number	Percent	Number	Percent	Number	Percent
1	848	63.5	692	66.9	1,540	65.0
2	306	22.9	235	22.7	541	22.8
3+	181	13.6	108	10.4	289	12.2
All	1,335	100.0	1,035	100.0	2,370	100.0
Mean	1.6		1.5		1.5	
Std. Dev.	1.0		1.0		0.9	

Table 2.4: Distribution of number of self-employment jobs per person

Duration (month)	Men		Women		All	
	Number	Percent	Number	Percent	Number	Percent
Less than 12	636	30.1	518	33.3	1,154	31.5
12 - 35	701	33.2	561	36.1	1,262	34.4
36 - 59	249	11.8	210	13.5	459	12.5
60+	527	24.9	266	17.1	793	21.6
All	2,113	100.0	1,555	100.0	3,668	100.0
Mean	45.4		34.9		41.0	
Std. Dev.	56.2		41.9		50.9	

Note: If job spell is right-censored, the last interview date is regarded as ending date. For jobs that begin before age 22, the actual start date is used.

Table 2.5: Distribution of durations of self-employment jobs

	Men		Women	
Industry	SE	Prior to SE	SE	Prior to SE
Agriculture	9.9	5.2	1.8	1.2
Construction	27.0	19.1	1.5	1.7
Manufacturing	3.6	10.7	2.3	7.4
Transportation/Communication/Utility	7.1	8.8	2.4	4.5
Trade (wholesale, retail)	9.8	12.5	12.1	14.3
Finance, insurance, or real estate	3.5	3.7	2.6	4.1
Business services	8.5	7.1	11.1	7.4
Repair services	10.6	4.8	1.0	1.1
Personal services	5.8	6.9	27.5	17.0
Private Household	2.3	0.6	20.8	7.3
Professional Services	3.4	1.7	3.7	3.1
Health Service	1.0	1.7	3.2	7.6
Other Services	5.2	8.0	7.7	14.0
N/A (Industry)	2.3	9.3	2.4	9.4
All	100.0	100.0	100.0	100.0
Number of observations	2,113		1,555	

Table 2.6: Distribution of industries of self-employment jobs

	Men		Women	
	Change	Stay	Change	Stay
Industry change (percent)	65.5	34.5	73.9	26.1
Average duration (months)	38.0	50.3	31.9	39.8
Number of jobs	1,873		1,373	

Note: For this table, I exclude 300 self-employment jobs that are the first jobs held by ever self-employed workers during 19-year window, 82 jobs with no industry information, and 40 jobs of which preceding wage job industries are not identified from 3,668 self-employment jobs.

Table 2.7: Percent of industry change and duration of self-employment jobs

	Men		Women	
	NE	WE	NE	WE
Employment status (percent)	36.6	63.4	59.6	40.4
Average duration (months)	38.9	49.2	30.0	42.3
Industry change (percent) [a]	69.2	63.6	74.7	72.9
Number of observations	2,113		1,555	

[a] The number of self-employed jobs is the same as the number in Table 2.7. From 3,668 self-employment jobs, I exclude 300 jobs that are the first jobs held by ever self-employed workers during 19-year window, 82 jobs with no industry information, and 40 jobs of which preceding wage job industries are not identified.

Table 2.8: Employment status prior to self-employment, industry changes and duration of self-employment

	Men				Women			
	Self-employment		Wage employment		Self-employment		Wage employment	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Job characteristics								
Hourly earning ($)[a]	20.91	47.80	13.01	28.04	13.62	32.06	10.38	19.62
[Median]	[15.17]		[9.93]		[8.09]		[8.27]	
Duration of job (months)	45.36	56.23	30.58	46.67	34.93	41.88	30.38	44.39
1 if job is incorporated	0.11				0.08			
1 if industry is								
Agriculture	0.10		0.05		0.02		0.02	
Construction	0.27		0.15		0.02		0.01	
Manufacturing	0.04		0.17		0.02		0.10	
Transportation/Communication/Utility	0.07		0.09		0.02		0.05	
Trade	0.10		0.14		0.12		0.16	
Finance	0.04		0.03		0.03		0.07	
Business services	0.08		0.08		0.11		0.08	
Repair services	0.11		0.03		0.01		0.00	
Personal services	0.06		0.09		0.28		0.15	
Private Household	0.02		0.00		0.21		0.02	
Professional	0.03		0.01		0.04		0.03	
Health Service	0.01		0.03		0.03		0.13	
Other Services	0.05		0.10		0.08		0.17	
N/A (Industry)	0.02		0.01		0.02		0.01	
Labor market experience								
Percent of time nonemployed[b]	23.59		27.53		40.27		35.45	
Percent of time working in same industry[b]	24.17		21.84		13.34		18.63	
Age at start[b]	31.05	5.96	29.46	5.86	31.81	5.56	29.70	6.03

Continued

Table 2.9: Characteristics of self-employment jobs and wage jobs

Table 2.9 Continued

	Men				Women			
	Self-employment		Wage employment		Self-employment		Wage employment	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Personal characteristics								
Years of schooling	12.64	2.44	12.57	2.35	13.10	2.40	13.02	2.24
1 if married	0.50		0.41		0.69		0.50	
1 if divorced	0.11		0.10		0.12		0.14	
1 if children in the household	0.40		0.32		0.73		0.57	
Number of obsns	2,113		27,968		1,555		26,105	

Note: All variables are defined at the beginning of a job spell

[a] Deflated by the CPI-U and expressed in 2002 dollars..

[b] Measured from 22nd birthday to start of the self-employment spell.

CHAPTER 3

RISK, LIQUIDITY CONSTRAINTS AND SELF-EMPLOYMENT

3.1 Introduction

The number of self-employed workers in the U.S. has grown dramatically in recent decades. Estimates show that over ten percent of the labor force is self-employed when incorporated businesses are counted (Hipple 2004) and a quarter of young men are self-employed at some time in their early careers (Ferber and Waldfogel 1998). Because self-employment is often considered a way for disadvantaged workers to achieve economic prosperity and upward mobility (Fairlie 2004), these rising rates have sparked policy makers' and researchers' interest in the determinants of self-employment.

In this paper, I specify a theoretical model that illustrates how individual risk tolerance and liquidity constraints affect the self-employment entry decision. Using repeated measures of personal assets and individual risk preference from the 1979 National Longitudinal Survey of Youth (NLSY79), I then identify the empirical importance of these two factors in the decision of male workers to enter self-employment. My study is by no means the first to focus on risk tolerance and liquidity constraints as key determinants of self-employment decisions. However, my approach is unique in that I control for risk tolerance and assets simultaneously, consider the potential endogeneity of both factors, and determine whether the estimates are sensitive to how risk tolerance is measured.

A key feature of my analysis is that I use a measure of risk tolerance that increases with individual asset levels. This innovation proves to be crucially important for correctly assessing the effect of liquidity constraints on the decision to enter self-employment. Starting a business often requires liquidity, but if the credit available to a worker is constrained by the level of assets he holds, a low level of assets can deter a worker from starting a business. However, a positive relationship between assets and self-employment does not necessarily reflect the impact of borrowing constraints because absolute risk tolerance increases with assets under decreasing absolute risk aversion (Cressy 2000). Without accounting for the positive effects of assets on individual risk attitudes, the effect of liquidity constraints on business entry is overestimated. Indeed, I find that assets have no effect on the probability of entering self-employment when I control for absolute risk tolerance, while their estimated effect is positive if I substitute a measure of risk tolerance that is independent of assets or omit risk tolerance altogether from the model. These findings augment the results of Hurst and Lusardi (2004), who were the first to refute the conventional wisdom that liquidity constraints form a barrier to entering self-employment. My results demonstrate that the significant effect of asset levels on self-employment found in earlier studies (Evans and Jovanovic 1989; Holtz-Eakin et al. 1994; Lindh and Ohlsson 1996) reflects their failure to control for absolute risk aversion.

Another important feature of my estimation strategy is that I address the issues of measurement error and age variation in self-reported risk tolerance by using multiple responses to identical "income gamble" questions asked in the NLSY79. While individual risk tolerance has long been considered a key characteristic of entrepreneurs

(Knight 1921), empirical research has been limited by a lack of data on individual risk preference—and even when data are available, empirical researchers have typically assumed that individual risk attitudes are inherently fixed (Cramer *et al.* 2002; Guiso and Paiella 2005; Dohmen *et al.* 2005). Following Barsky *et al*. (1997) and Kimball *et al.* (2005), I correct my measure of risk tolerance for measurement error. In light of arguments that individual risk tolerance is likely to decrease with age (Morin and Suarez, 1983; Bakshi and Chen 1994; Sahm 2006), I also account for age-variation in my measure of risk tolerance. While the latter feature proves to have no effect on the estimates, I find that the estimated effect of risk tolerance on the probability of entering self-employment is dramatically understated if measurement error is not taken into account.[5]

I also account for the potential endogeneity of individual asset levels and risk tolerance (which is a function of assets) by using changes in housing prices as an exogenous source of variation and allowing their effects to differ by age and race. Because asset levels not only represent credit availability but may also reflect unobserved traits that affect business entry, many previous studies have attempted to find instruments for assets (Holtz-Eakin, Joulafaian, and Rosen 1994; Lindh and Ohlsson 1996; Blanchflower and Oswald 1998). Recently, Hurst and Lusardi (2004) used the variation in regional housing capital gains as instruments for individual asset levels. However, the

[5]I also compare the performance of the direct measure of risk tolerance based on income gamble questions to an indirect measure proposed by Fairlie (2002) based on previous drug-dealing experience. I find that the estimated effect of "direct" risk tolerance on the probability of entering self-employment is invariant to whether the "indirect" measure is added to the model. However, the drug-dealing measure has a significant, independent effect on self-employment, which indicates that it captures other important attributes such as a taste for autonomy or restricted labor market opportunities.

effects of house price changes may differ across segments of the population: while increased housing values positively affect the net assets of homeowners (who are typically older and more affluent than non-homeowners), it increases the housing costs for non-homeowners and produces negative effects on their net assets. Further, Li and Yao (2005) argue that house price appreciation benefits older homeowners but hurts young homeowners because young owners expect to upgrade their houses as they age and have larger families. To capture these different effects of housing price changes on individual assets, I use interactions between the change in house price and age and race as my instruments.

Like Hurst and Lusardi (2004), I find that using housing price variation as instruments eliminates the positive, estimated relationship between net asset levels and the probability of entering self-employment. However, as already noted, I also eliminate the positive effect of net assets simply by adding a measure of absolute risk tolerance to my set of covariates (and treating both assets and risk tolerance as exogenous). The bottom line is that a lack of assets is not a major deterrent to starting a business. While this finding corroborates the results of Hurst and Lusardi (2004), I also find that the reason earlier studies find a positive relationship between assets and self-employment is because assets are positively correlated with (omitted) absolute risk tolerance. Adding a measure of absolute risk tolerance to the model precludes the need to find suitable instrumental variables for assets.

The rest of my "bottom line" is that individual risk tolerance plays an important role in the self-employment entry decision. An increase in absolute risk tolerance from the 25th percentile to the 95th percentile increases the predicted probability of entry into

self-employment by 35%. However, using a one-time measure of risk tolerance attenuates its estimated effect by a staggering 87% because measurement error cannot be netted out. This result underscores the need to use multiple responses in order to correct self-reported risk tolerance for reporting error.

3.2 Background

3.2.1 Measuring risk tolerance

Individual risk tolerance has long been regarded to be a key characteristic of entrepreneurs (Knight 1921; Kihlstrom and Laffont 1979). However, empirical studies that assess this view have been limited because direct measures of risk preference are hard to obtain. A few researchers have skirted this data constraint by using measures of "risky behavior" to construct indirect measures of risk preference. For example, Tucker (1988) uses self-reported measures of seat belt use, auto and health insurance coverage, and cigarette smoking while Fairlie (2002) and Francis and Demirap (2006) use self-reports on drug use and drug dealing experience. All three studies use these self-reported behavioral measures as proxies for risk attitudes or to construct a measure of risk preference for the purpose of explaining who enters self-employment. Estimates based on these indirect measures do not always lead to the same conclusion. While Tucker (1988) finds no effects of risk attitudes on being self-employed, other studies (Fairlie 2002; Fancis and Demirap 2006) find that risk tolerance has a significant positive effect on the likelihood of being self-employed. Of course, these indirect measures may also identify individual attributes other than risk preference such as desire for autonomy and entrepreneurial skills (Fairlie 2002). I am able to assess this conjecture by including

Fairlie's "drug-dealing" measure along with a direct measure of risk tolerance (described below) in my empirical model, and determining whether the two measures have independent effects on the probability of entering self-employment.

Recently, a number of surveys in different countries have attempted to evaluate individual risk attitudes by including direct questions on the respondent's willingness to participate in a hypothetical lottery or risky investment (Cramer *et al*. 2002; Guiso and Paiella 2005; Dohmen *et al.* 2005). With this type of measure, Cramer *et al.* (2002) look at the link between measured risk tolerance and entrepreneurship and find a small, positive relationship between the two. However, they (along with Guiso and Paiella 2005 and Dohmen *et al.* 2005) assume that respondents report their preferences without error and that individual risk attitudes are inherently fixed over the life-cycle. More to the point, they are compelled to make these assumptions because they have only one response for each sample member.

Longitudinal data on risk tolerance are preferred to single responses because they allow researchers to assess the role of reporting error and, more generally, the extent to which risk tolerance changes over time. Barsky *et al.* (1997) developed a set of questions about hypothetical income gambling that were fielded in the 1992 wave of the Health and Retirement Study (HRS).[6] In 1994, 10% of respondents who answered the risk questions in 1992 were asked them again; this survey design enabled Barsky *et al.* (1997) to account explicitly for survey measurement error.

[6] These questions are described in detail in Section 3.5.

In 1993 and 2002, the 1979 National Longitudinal Survey of Youth (NLSY79) asked *all* respondents a set of risk questions identical to those used in the HRS.[7] Because the NLSY79 provides two responses from identical individuals, it is possible to construct a measure of risk tolerance that controls for measurement error, as in Barsky *et al*. (1997) and Kimball *et al.* (2005). As I discuss in Section 3.5, I extend their approach by relaxing their assumption that individual risk tolerance is fixed over time for a given individual. That is, I drop the assumption that within-person variation in reported risk tolerance is *only* due to reporting error, and instead allow for aging effects. While the HRS is designed to study the retirement, investment and savings behavior of people over the age of 50, data from the NLSY79 are better-suited to examine individual behavior in early to mid life. To my knowledge, my study is the first to exploit the double responses available in the NLSY79 to construct a measure of risk tolerance that accounts for both measurement error and age variation.

3.2.2 Liquidity constraints and assets

Liquidity constraints appear to be the most frequently cited determinant of self-employment (Evans and Jovanovic 1989; Holtz-Eakin *et al*. 1994; Lindh and Ohlsson 1996) and are at the core of policy-makers' concerns about the ability of low- and middle-income individuals to launch small businesses. A theoretical model by Evans and Jovanovic (1989) posits that an increase in personal assets raises the probability of self-employment only if credit constraints are binding, assuming a risk neutral, profit

[7] The Panel Study of Income Dynamics (PSID) also used the same income gambling questions in a 1996 supplement. However, the questions were asked only *once*, of respondents who were employed.

maximizing agent. If the credit available to a worker is constrained by the level of assets he holds, a low level of assets can deter a worker from starting a business. An increase in assets relaxes liquidity constraints and raises the probability of self-employment.

A large number of studies have tested this argument empirically. However, empirical tests are complicated by the fact that the level of wealth may be the consequence of a successful business and that, as a result, asset accumulation is not exogenous to the self-employment entry decision. In light of these simultaneity issues, a large number of empirical studies have attempted to control for the endogeneity of assets. They have used various instruments and proxies such as inheritance (Blanchflower and Oswald 1998; Holtz-Eakin *et al*. 1994), gains from lotteries (Lindh and Ohlsson 1996), and house price appreciation (Hurst and Lusardi 2004; Fairlie and Krashinsky 2006).[8]

While most empirical studies have supported the notion that liquidity constraints play a key role in the self-employment entry decision, Hurst and Lusardi (2004) cast doubt on the importance of liquidity constraints by finding (using 1989 and 1994 PSID data) no relationship between wealth and entrepreneurship except at the top of the wealth distribution. They argue that the positive relationship between wealth and self-employment entry for the extremely wealthy suggests that liquidity constraints are unimportant for would-be *small business* owners.

Even if the variation in assets used for identification is exogenous, a positive relationship between assets and self-employment does not necessarily provide evidence of borrowing constraints. Cressy (2000) argues that a person without credit constraints is more likely to choose self-employment over wage work as he becomes wealthy as long as

[8] While Hurst and Lusardi (2004) use house price appreciation as an instrument for net assets, Fairlie and Krashinsky (2006) include it directly in their self-employment entry equation.

absolute risk aversion is a decreasing function of wealth. For my purposes, the lesson to be taken from Cressy's theoretical argument is that the relationship between liquidity constrants and entry into self-employment cannot be identified using asset data only because absolute risk tolerance and asset levels are positively related. It is necessary to control for both absolute risk tolerance (which increases with assets) and assets in order to disentangle the direct effects of liquidity constraints from the indirect effects of assets.

In a recent study, Kan and Tsai (2006) include wealth and a one-time measure of relative risk aversion in a self-employment entry equation. They find that net assets have a positive effect on the probability of entering self-employment. While their study is the first to control for both assets and a "direct" measure of risk aversion in a model of self-employment entry, my analysis makes further progress by controlling for *absolute* risk tolerance. In addition, I use instrumental variables to control for the potential endogeneity of assets, account for measurement error and age variation in self-reported risk tolerance, and add an indirect measure of risk tolerance along with the direct measure. By incorporating each of these innovations in sequence, I am also able to assess the relative importance of each one.

3.3 Model

In this section, I discuss the effects of risk tolerance and liquidity constraints on the self-employment decision by modifying the model of Kihlstrom and Laffont (1979) to include capital investment. I consider a situation where an individual who currently works for an employer decides whether to choose self-employment or continue with his

"wage employment."[9] As long as the individual works for an employer, he receives a constant wage with certainty. If he chooses self-employment, he must decide how much to invest in the new enterprise and then receive an uncertain return from that investment. In short, I assume that self-employment requires some form of capital investment, and that it is riskier than wage employment.

The individual has a utility function $U(C, \gamma)$ that satisfies $U_C>0$ and $U_{CC}\leq 0$, where C is his consumption of composite goods and γ represents his degree of absolute risk tolerance ($-U_C/U_{CC}$), which is the reciprocal of the Arrow-Pratt measure of absolute risk aversion. Note that the individual's degree of *relative* risk tolerance (ρ) is $-U_C/(C\cdot U_{CC})$, or the reciprocal of the Arrow-Pratt measure of relative risk aversion. I assume that the individual has constant relative risk aversion (CRRA), which means ρ is independent of C.[10] Because absolute risk tolerance is simply relative risk tolerance multiplied by C, it follows that the individual's degree of absolute risk tolerance increases in C. Throughout this analysis, I use the individual's current asset level (A) as a proxy for C. Thus, we have the relationship $\gamma=\rho A$ and the assumption that *absolute* risk tolerance increases as *asset* levels increase. I also assume that the degree of both absolute and relative risk tolerance varies across individuals.

[9] I do not consider other types of transitions such as non-employment to self-employment and self-employment to wage employment. Adding those transitions would require a multi-state, multi-stage sequential choice model in which the unobserved factors are correlated across alternatives and across stages. I leave these extensions for future research.

[10] In order to obtain the results in this section, I only need to assume decreasing absolute risk aversion (DARA), which is a weaker assumption than CRRA. However, I assume CRRA because I use income gamble questions that are designed to compute individual risk tolerance using the CRRA assumption; See in section 3.5.

I assume that each individual's level of assets (A) is determined prior to the self-employment decision. However, as I discuss below, assets are not strictly exogenous because unobserved personal characteristics that affect asset accumulation will also influence the decision to enter self-employment. Because the degree of absolute risk tolerance is a function of assets it, too, will be treated as endogenous. These issues are pursued in Sections 3.3.3 and 3.4.

When an individual chooses self-employment, his earnings are determined by

$$y = \pi(k, \varepsilon),$$

where k is his level of capital investment and ε is a stochastic component. I assume that all individuals face the identical profit function π and draw realizations of ε from a common distribution. The profit function represents what he eventually receives after subtracting the cost of capital investment from the revenues. These assumptions are compatible with the goal of my model, which is to use a simple, static decision-making framework to illustrate how variation in risk tolerance and assets affect the decision to enter self-employment. However, as I discuss in Section 3.3.3, individual differences in entrepreneurial skill (*i.e.,* heterogeneity in the profit function π) is a factor I consider when discussing the potential endogeneity of personal assets.

Each individual faces the credit limit

$$k \leq \lambda A$$

where λ is larger than one and is the same for every individual. Let k^* be the individual's optimal level of capital investment that maximizes his expected utility $EU(A+\pi(k, \varepsilon), \gamma)$.

He will invest k^* if it is less than the credit limit λA; otherwise, he invests λA. Thus, an individual chooses to be self-employed if

$$EU(A+\pi(k, \varepsilon), \gamma) - U(A+w, \gamma) \geq 0,$$

where w is the (certain) wage associated with wage employment.

3.3.1 Individual absolute risk tolerance and self-employment

To see how an individual's level of risk tolerance affects his choice, I first consider the reservation wage w_γ^* that leaves him indifferent between choosing self-employment and choosing wage employment. That is,

$$EU(A+\pi(k, \varepsilon), \gamma) = U(A+w_\gamma^*, \gamma). \tag{3.1}$$

I consider two individuals who are identical except that individual 1 is more tolerant to risk than is individual 2 ($\gamma_1 > \gamma_2$). By Pratt's (1964) theorem, the individual with a higher degree of absolute risk tolerance has a higher reservation wage ($w_{\gamma_1}^*(k) > w_{\gamma_2}^*(k)$) for every k.[11]

Which of these two individuals is more likely to choose self-employment? Let k_2 be the level of capital investment that individual 2 chooses when he is self-employed and $w_{\gamma_2}^*(k_2)$ be the corresponding reservation wage. Given the arguments made in the preceding paragraph, it is clear that

$$EU(A+\pi(k_2, \varepsilon), \gamma_1) = U(A+w_{\gamma_1}^*(k_2), \gamma_1) > U(A+w_{\gamma_2}^*(k_2), \gamma_1). \tag{3.2}$$

[11] According to the theorem, a person with higher risk tolerance has a lower risk premium to the risk than does a person with lower risk tolerance. This also implies that the certainty equivalent of risky income is higher for the person with higher risk tolerance.

The equality in (3.2) is simply a restatement of (3.1), and the inequality follows from the fact that $w^*_{\gamma_1}(k_2) > w^*_{\gamma_2}(k_2)$ and utility is a monotonic function of w. Letting k_1 be individual 1's optimal capital investment, it is clear that

$$EU(A+\pi(k_1, \varepsilon), \gamma_1) \geq EU(A+\pi(k_2, \varepsilon), \gamma_1) \tag{3.3}$$

because k_1 must leave individual 1 no worse off than the nonoptimal investment level k_2. From (3.2) and (3.3), it is directly apparent that

$$EU(A+\pi(k_1, \varepsilon), \gamma_1) > U(A+w^*_{\gamma_2}(k_2), \gamma_1).$$

That is, individual 1 chooses self-employment if he is offered the reservation wage of person 2, $w^*_{\gamma_2}(k_2)$. This relationship implies that when faced with the same wage alternative, the individual who is more tolerant to the risky income is more likely to choose self-employment than is the less risk tolerant individual. In short, the probability of being self-employed is an increasing function of absolute risk tolerance (γ), all else equal.

3.3.2 Personal assets and self-employment

To determine how asset levels affect the decision to enter self-employment, I again consider an individual who is indifferent between self-employment and wage work. From equation (1), we see that the change in the value of self-employment in response to a change in assets is

$$\frac{d(EU-U)}{dA} = \frac{\partial EU}{\partial k}\frac{\partial k}{\partial A} + \left[\frac{\partial EU}{\partial A} - \frac{\partial U}{\partial A}\right]_{k=const.} \tag{3.4}$$

A change in assets affects the value of self-employment via its affect on investment levels (shown by the first right-hand side term in (3.4)) and also via its effect on preferences (the second term in (3.4)). The second term in (3.4) is positive by Jensen's inequality if marginal utility is convex ($U_{CCC} > 0$)—and marginal utility is convex as long as absolute risk tolerance increases with assets ($d\gamma/dA>0$) which, as discussed earlier, I assume following Cressy (2000).[12] The intuition is that an increase in assets raises the degree of absolute risk tolerance, thereby raising the value of the uncertain income relative to the certain income.

The first term in (3.4) is positive only if the capital investment is constrained by the credit limit. Otherwise, the term is zero because expected utility is already maximized at the optimal level of capital, k^* where $\frac{\partial EU}{\partial k^*} = 0$. If the capital investment is constrained by the credit limit (λA), the increase in assets enables the individual to expand his capital investment and raise the value of self-employment.

To sum up, the total effect of assets on the self-employment decision is decomposed into two parts. First, an increase in assets raises the value of self-employment by relaxing the liquidity constraint. This effect exists only for those who are constrained from optimal investment due to their insufficient credit limits. Second, it raises the value of self-employment by raising the level of absolute risk tolerance. If the degree of absolute tolerance is ignored in the empirical analysis, the effect of liquidity

[12] That is,

$$\frac{d\gamma}{dA} = \frac{d(-U_C / U_{CC})}{dA} = \frac{-(U_{CC})^2 + U_C U_{CCC}}{(U_{CC})^2} > 0$$

which implies the convexity of marginal utility ($U_{CCC} > 0$).

constraints cannot be distinguished from the effect of increasing risk tolerance. Specifically, it is possible to disentangle the effect of liquidity constraints from the effect of assets *only by modeling risk tolerance as an increasing function of assets.*

3.3.3 The endogeneity of assets and risk tolerance

The basic model is static and does not explicitly describe the determination of personal assets. However, the level of personal assets is likely to be endogenous to the self-employment decision. It is documented that entrepreneurs own high levels of assets (Gentry and Hubbard 2004), which may reflect the fact that the level of assets is an outcome of past self-employment decisions. It is also possible that there are unobserved factors that help determine assets prior to the self-employment decision. For example, traits inherited from one's parents, including ability, entrepreneurial spirit and investing skill, may contribute to an individual's wealth and also drive him to enter self-employment (Dunn and Holtz-Eakin 2000). In addition, the would-be entrepreneur is likely to save a high level of assets prior to starting a business (Buera 2006). Even if the model assumes that self-employment is a "one time" endeavor, such traits could affect assets and the self-employment entry decision via heterogeneity in the distribution from which the shocks are drawn, or via heterogeneity in the profit function.

3.4 Econometric specification

In the previous section, I demonstrated how an individual's levels of absolute risk tolerance and assets will affect his task of choosing between self-employment and wage employment. I also argued that asset levels may be endogenous to this decision, and that

absolute risk tolerance is itself a function of assets. To assess the empirical effects of risk tolerance and asset levels on the self-employment probability, I estimate an equation for the probability of entering self-employment along with an asset equation.

Focusing first on the self-employment decision, I consider a discrete choice model of the transition from wage employment to self-employment. The latent variable S_{it}^{*} represents the value of self-employment relative to wage work for individual *i* at time *t.* I assume this can be approximated by the following linear function:

$$S_{it}^{*} = \beta_1 \gamma_{it} + \beta_2 A_{it} + X_{it}\beta_3 + Z_{it}\beta_4 + u_{it} \tag{3.5}$$

where γ_{it} is absolute risk tolerance, A_{it} is the level of personal assets, X_{it} is a vector of variables that contains age, race dummies, and a constant, Z_{it} is a vector of other individual characteristics, job characteristics, and environmental factors, and u_{it} is unobserved factors that may be correlated with A_{it}; because γ_{it} is simply relative risk tolerance multiplied by assets it, too, may be correlated with u_{it}. I model the probability that S_{it}^{*} is larger than zero, which means the individual enters self-employment within a given interval.

Following the discussion in Section 3.3, I expect the estimate of β_1 to be positive because the relative value of self-employment increases with absolute risk tolerance. I expect the estimate of β_2 to be positive only if the startup capital investment is constrained by individual asset levels (*i.e.* if liquidity constraints exist). If absolute risk tolerance is omitted from equation (3.5), then β_2 represents the direct effect of assets (via the role of liquidity constraints) and the indirect effect of assets through their effect on absolute risk tolerance.

The equation that determines personal assets is

$$A_{it} = X_{it}\pi_1 + Z_{it}\pi_2 + X_{it}h_{it}\phi + \varepsilon_{it} \tag{3.6}$$

where X and Z are the same vectors of observables included in equation (3.5), h_{it} represents the appreciation in housing prices in the state of residence of individual i at time t, and ε_{it} represents unobserved factors. I use regional house price change and its interactions with age and race, $X_{it}h_{it}$, as my instruments to address the fact that house price appreciation has different effects among different demographic groups. The instruments are assumed to be uncorrelated with unobserved factors (u_{it}) that determines self-employment entry decision.

To close the specification of the model, I assume that the disturbances in (3.5) and (3.6) are jointly normally distributed: $(u_{it}, \varepsilon_{it}) \sim N(0, \Sigma)$, where

$$\Sigma = \begin{pmatrix} 1 & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}.$$

The log likelihood function is

$$L = \sum_i \sum_t \log[f(S_{it} = 1, A_{it})^{S_{it}} \cdot f(S_{it} = 0, A_{it})^{1-S_{it}}],$$

where f is the joint density function of self-employment entry and asset level of individual. To obtain correct standard errors for statistical inference, I use sandwich-type "Huber-White standard errors" that account for non-independence of error terms across observations for a given individual.

3.5 Data

3.5.1 Sample Selection

I use data from the 1979 National Longitudinal Survey of Youth (NLSY79). The NLSY79 began in 1979 with a nationally representative sample of 12,686 individuals who were between ages 14 and 22 at their first interview. Interviews were conducted annually from 1979 to 1994 and biennially thereafter. The original sample consists of three subsamples: a sample of 6,111 individuals representing the civilian population born between 1957 and 1964, a supplemental sample of 5,295 black, Hispanic and economically disadvantaged non-Hispanic, non-black youth, and a sample of 1,280 individuals who enlisted in the military before September 1978.

In selecting a sample for analysis I focus only on men, who account for 6,403 of the original sample members, because self-employment decisions of women are arguably different from those of men in various dimensions (Hundley 2000, Taniguchi 2002). Second, I drop 1,849 individuals who did not provide responses to risk questions in 1993 or in 2002. (I describe these questions in detail in Section 4.5.3.) Third, I drop 264 individuals who did not report any wage job with information on wages and hours worked during the observation period that I define in Section 3.5.2. Third, I eliminate 464 individuals who were self-employed prior to holding the first wage job identified by the preceding selection rule. This allows me to focus my analysis on first transitions from wage employment to self-employment. Fourth, I drop 51 individuals who contribute no observation with valid information on state of residence, urban status, and local unemployment rate. The resulting sample consists of 3,775 respondents: 1,171 blacks, 748 Hispanics, and 1,856 individuals who are nonblack and non-Hispanic.

3.5.2 Entry into self-employment

In estimating the probit model described by equation (3.5), I use explanatory variables (γ, *A, X,* and *Z)* reported in period t to explain the probability of entering self-employment *within* the next *two* years (*i.e.,* by period t+2). I use two-year intervals because the survey becomes biennial in 1994. While most of my explanatory variables are available in every survey year, respondents report detailed asset information only in 1985-90, 1992-94, 1996, 1998, 2000, and 2004—in other words, assets are *not* reported in 1979-84, 1991, and 2002.[13] Therefore, I only use two-year intervals that begin in an "asset year:" 1985-1987, 1986-1988, 1987-1989, 1988-1990, 1989-1991, 1990-1992, 1992-1994, 1993-1995, 1994-1996, 1996-1998, 1998-2000, 2000-2002.

The availability of asset data also determines how I define the observation window referred to in the preceding subsection. Because I ultimately consider transition intervals that begin no earlier than 1985 and end no later than 2002, these years define my observation period with the following exceptions. First, I also set an exogenous career start date at age 22 to avoid picking up jobs held while in school. The imposition of this career start date only affects respondents who were 14-15 in 1979. Thus, the start of my observation window is either the 1985 interview or the respondent's 22nd birthday, whichever is later. Second, respondents who drop out of the survey before 2002 are only seen until their last interview date. Third, because I am modeling *first* transitions into

[13] Information used to construct another key variable, relative risk tolerance (γ), is collected even more irregularly than assets in the NLSY79. I explain in Section 3.5.3 my method for imputing values of this variable.

self-employment, respondents who enter self-employment are only followed until this transition occurs.

To determine the self-employment status of each respondent on each job reported during the observation window, I use the "class of worker" information reported with regard to his "current or last job." The class of worker question from 1979 to 1993 is:

Are/Were you... (Interviewer reads categories below)

1. an employee of a private company, business or individual for wages, salary or commission, or

2. a government employee, or

3. self-employed in own business, professional practice, or farm, or

4. working without pay in a family business or farm?

In 1994, the coding system was changed to include work for non-profit organizations as a separate category, and the question became:

Are/Were you employed by government, by a private company, or a non-profit organization, or are/were you self employed or working in a family business?

In 2002, in addition to the class of worker question respondents were also asked a series of questions that determine the type of job (traditional, non-traditional, or self-employed). To maintain comparability across years, I ignore this additional information in 2002 and use the "class of worker" definition for all years. I consider respondents to be self-employed only if they report self-employment as their "class;" those who were working without pay in a family business are not counted as self-employed. I consider all other jobs to be wage employment.

A sample member contributes an observation to the sample used to estimate the probit whenever he reports a "current or last" job in period *t* and I classify that job as wage employment. I consider him to make a transition to self-employment in the next two years if *any* new job reported no later than period *t*+2 is classified as self-employment. If no new job is classified as self-employment or if no new job is reported, I consider him to have made a wage-to-wage transition. In other words, wage-to-wage transitions include non-transitions for those individuals who maintain their wage employment over the two-year interval.[14]

The 3,775 workers in my sample are observed making 27,650 two-year transitions during the observation window—an average of 7.3 per person. Table 3.1 shows that almost 5% of these transitions are from wage employment to self-employment. Because sample members have multiple opportunities to enter self-employment between 1985 and 2002, far more than 5% eventually become self-employed. As shown in Table 3.1, 931 of the 3,775 sample members (24.7%) enter self-employment.

3.5.3 Measure of risk tolerance

In 1993 and 2002, NLSY79 respondents were asked a series of questions designed to measure their relative risk tolerance. As noted in Section 3.5.1, the 3,775 men in my sample were selected in part because they answered these questions in at least one year. Of these 3,775 men, 3,115 (82.5%) provided responses in both 1993 and 2002;

[14] Although respondents are observed until their first entry into self-employment or their last interview, it is possible to contribute more than one wage to self-employment transition to my sample. For example, a worker who enters self-employment in 1989 can contribute a "wage to self" transition for 1987-89 and also for 1988-90. On average, workers who enter self-employment have 1.4 transitions to self-employment.

another 591 men answered the risk questions in 1993 only, and the remaining 69 sample members answered these questions in 2002 only.

The first risk tolerance question is as follows:

> *Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance that it will double your (family) income and a 50-50 chance that it will cut your (family) income by a third. Would you take the new job?*

If the respondent answers "yes" to this question, he is asked a similar question, but the risk becomes "*a 50-50 chance that it will cut your (family) income by a half*." If he says "no" to the first question, he faces a different follow-up question where the risk becomes "*a 50-50 chance that it will cut your (family) income by a fifth*."

I begin by summarizing the "raw" data to learn how responses differ across individuals and over time for the same individuals. To do this, I place each respondent into one of four categories ranging from least tolerant (category 1) to most risk tolerant (category 4) based on their responses to the two questions. These categorical responses are summarized in Table 3.2. Looking first at the distribution of responses for each year, I find that the largest portion of the sample (43.2% in 1993 and 53.2% in 2002) is categorized as the least risk tolerant (category 1), meaning they decline all gambles. However, the second most common category in both years is the most risk tolerant (category 4) meaning they accept all gambles; 28.5% and 19.9% of men fall into this category in 1993 and 2002. Clearly, there is substantial heterogeneity in risk tolerance in the sample.

The right-most columns in Table 3.2 show the distribution of 2002 responses by 1993 categories. Among those who answered the income gamble questions twice, the percent remaining in the same category in both years is 64.7%, 15.3%, 22.5%, and 30.4% for respondents initially placed in category 1, 2, 3 and 4, respectively. Overall, only 42% of these men are in the same category in both years. Another noteworthy feature of these data is that within all categories in 1993, the largest portion of men rejects all gambles in 2002. For example, even among men who are the most risk tolerant (category 4) in 1993, 41.6% are in category 1 in 2002 compared to only 30.4% who remain in category 1. This large degree of intertemporal inconsistency can be due in part to reporting error, but the systematic nature of the cross-year inconsistency suggests that people become less risk tolerant as they age. Thus, it is important to construct a measure that accounts for reporting error and the age-varying nature of risk tolerance.

My task is to convert responses to the income gamble questions into a measure of absolute risk tolerance (γ) that can be used in estimating equation (3.5). In carrying out this task, I must satisfy three objectives. First, I must convert the categorical responses to a continuous measure of risk tolerance. Second, I must account for the fact that risk tolerance is reported with error, as suggested by the intertemporal variation in responses seen in Table 3.2. Third, I must account for the age-varying nature of individual risk tolerance that is also suggested by the responses summarized in Table 3.2. Barsky *et al.* (1997) and Kimball *et al.* (2005) propose a method for achieving the first two objectives.

I follow their method, and simply modify it to account for the possibility that responses vary over time due to aging as well as reporting error.[15]

Following Barsky *et al.* (1997) (and as detailed in Section 3.3), I assume individuals have the following constant relative risk aversion (CRRA) utility function:

$$U_{it} = \frac{C_{it}^{1-1/\rho_{it}}}{1-1/\rho_{it}}.$$

Although we do not observe each individual's degree of relative risk tolerance (ρ_{it}) directly, we can infer the upper and lower bounds of these values from the reported responses to the income gamble questions. For example, the upper and lower bounds for those who accept the 50-50 chance that their income will be cut by a third but reject the 50-50 chance that their income will be cut by a half are determined by solving

$$U(C) \leq 0.5U(2C) + 0.5U(2/3C),\ \ 0.5U(2C) + 0.5U(1/2C) \leq U(C).$$

In this scenario, the corresponding lower and upper bounds of relative risk tolerance are 0.5 and 1, respectively. Table 3.3 presents these bounds for all four categorical responses (see also Barsky *et al.* 1997).

Next, I assume that the log of relative risk tolerance, the bounds of which we know as described above, can be modeled as follows:

$$\log \rho_{it} = \beta \text{Age}_{it} + \delta_i + \upsilon_{it} \tag{3.7}$$

where δ_i represents an unobserved, time-invariant, individual effect drawn from a normal distribution with mean μ and variance σ_δ^2, and υ_{it} is an idiosyncratic, mean zero error term with variance σ_υ^2 that reflects measurement error. I depart in an important way from

[15]Recall that absolute risk tolerance (γ) is simply relative risk tolerance (ρ) multiplied by assets (A). I discuss my asset measure in Section 3.5.4; the remainder of this section focuses on obtaining a "useable" measure of ρ.

Barsky *et al.* (1997) in specifying equation (3.7), for I allow relative risk tolerance to vary with *age* in addition to reporting error and individual traits that remain constant over time.

I estimate the parameters of (3.7) using a sample of 16,732 "income gamble" responses reported by the 9,153 respondents in the original sample. To carry out the estimation, I construct a log-likelihood function conditional on the boundary values of the reported risk tolerance categories and the respondent's age. I then compute maximum likelihood estimates of the parameters μ, σ_δ, σ_υ, and β. Because I have two responses for 7,579 of the 9,153 individuals, I am able to distinguish the distribution of fixed individual effects (σ_δ) from the survey measurement error (σ_υ).[16]

Table 3.4 shows the maximum likelihood estimates of the parameters in equation (7). Given the estimate for each error variance, I compute the additional statistic λ, which is the ratio of variation due to time-invariant, individual effects (σ_δ^2) to the total variation ($\sigma_\delta^2 + \sigma_\upsilon^2$). The value for λ *is* 0.26, which suggests that reporting error is substantial. In addition, the estimated β implies that relative risk tolerance decrease by 4.2% with each year of age and is statistically significant at 1%. Thus, it appears that aging is also an important source of variation in relative risk tolerance.

Using the estimated parameters shown in Table 3.4, I compute each individual's predicted relative risk tolerance ($\hat{\rho}_{it}$) using data on categorical risk responses and age. These predictions are made for each of the 27,650 person-interval observations that will be used to estimate the transition model. The final step is to multiply each predicted value by the individual's net asset level to obtain $\hat{\gamma}_{it} = \hat{\rho}_{it} A_{it}$; the asset measure is described in

[16] The one-response individuals only contribute to fitting the distribution of total variation, as is the case for Barsky *et al.* (1997).

Section 3.5.4.[17]

3.5.4 Net assets and instruments for net assets

I now turn to the second key covariate in my analysis: individual assets (*A*). For all survey years used in my analysis, the NLSY79 collects detailed information on respondents' assets. Respondents are asked to report whether they hold a variety of different types of assets. If they answer "yes," they are asked what that particular holding is worth. Respondents are asked the value of their homes, cash savings, stock holdings, trusts, business equity, car values, other possessions over $500, individual retirement accounts, tax deferred plans (*e.g.,* 401K, 403B), and certificates of deposit. They are also asked about the value of their mortgage, property debt, business debt, and other debts over $500.[18] To convert these category-specific asset values to a single, net asset value I simply sum the positive values and subtract the debts. However, I first impute missing values that arise when the respondent says he holds a particular asset, but does not report an amount. I linearly interpolate those values using values reported in the closest surrounding years, if such "bracketing" values are available. If the missing observation is not surrounded by two values, I estimate the linear time trend of the individual's net assets using the reported values from other years and extrapolate the missing value from this person-specific asset trend.

As I discussed in Section 3.4, net assets are potentially endogenous to self-employment decisions. In estimating the asset equation (equation 3.6), I use state- and

[17] Net assets are negative for 10% of the 27,650 observations. For these cases, I set the individual's absolute risk tolerance to zero. I also tried eliminating the observations with negative net assets but the estimated results were not affected in any important way.
[18] See Center for Human Resource Research (2004) for additional details.

year-specific values of the Conventional Mortgage Home Price Index (CMHPI), which is designed to measure the growth in housing prices within each state.[19] This index uses information on the value of mortgages for single-unit residences purchased by Freddie Mac or Fannie Mae; whenever the value of a house is observed repeatedly due to resale or reappraisal, the change in value contributes information to the computation of the index. Index values are available on a quarterly basis for every state for my entire observation period. I average these quarterly values over a year and compute yearly change to obtain one value for every state-year cell, and I then merge them with my NLSY79 data using information on the respondents' state of residence at each interview date.

The use of house price changes as instrumental variables for individual asset levels was proposed by Hurst and Lusardi (2004). The idea behind these instruments is that they provide exogenous regional variation in housing price changes that can be used to explain asset levels, given the fact that home values are often an important component of individuals' net assets. However, as they recognized, changes in house values are likely to be correlated with the economic conditions that affect self-employment decisions, so I control directly for local economic condition using variables described in the next subsection.

To extend the approach of Hurst and Lusardi (2004), who assume the house price changes affect all individuals within regions uniformly, I allow house price effects to differ across age and race within state-year cells. While a rise in housing value positively affects the net assets of homeowners in the area, it increases the housing costs for non-

[19] CMHPI data and documentation are at http://www.freddiemac.com/finance/cmhpi/.

homeowners and potentially produces negative effects on their net assets. Further, house price appreciation is expected to benefit older homeowners more than younger homeowners because young owners expect to upgrade their houses as they age and extend their families (Li and Yao 2005). To address these different aspects of house price appreciation, I use interactions between the house price index variable and age and race dummies as my instrumental variables.

3.5.5 Other variables

In addition to including respondent age and race dummies (black and Hispanic) in the transition model, I include an extensive array of variables referred to as vector Z in equation (3.5). The demographic controls in this vector are dummy variables indicating highest graded completed (less than 12, 13-15 or 16+, with 12 the omitted category), marital status dummies (married and divorced/separated, with never married the omitted category), and number of children.

To control for current job characteristics, I include wage rate on the current job,[20] average hours worked per week, years of tenure with the current employer and a dummy variable indicating tenure is less than one year, and dummy variables that indicate union status and whether the job is government-related work. I also include ten dummy variables indicating industry of employment.

Other person-specific variables include dummy variables that indicate whether the respondent has a health condition that limits the kind or amount of work he can perform, and the respondent's percentile score on the Armed Forces Qualification Test (AFQT);

[20] I multiply the average hourly wage rate by 2000 hours in order to "scale up" this measure to an annual amount for comparability with other dollar-valued variables.

AFQT scores are based on respondents' scores on the Armed Services Vocational Aptitude Battery, which was administered to NLSY79 respondents in 1980.

I also control for environmental factors that may affect self-employment decisions and local housing prices; the instrumental variables described in the preceding section are expected to be exogenous conditional on these factors. These environmental variables include a measure of the unemployment rate in the respondent's county of current residence and gross personal income per capita in his state of residence. In addition, I include dummy variables indicating whether the respondent lives in an urban area and in each broad Census region (northeast, north central and west, with south the omitted category). I also include a dummy variables indicating the year is before 1990.

Summary statistics for most of these regressors are provided in Table 3.5. All variables that measure dollar amounts (net assets, wage rates, and state per capita income) are deflated by the CPI-U and expressed in hundreds of thousands of 2002 dollars.

3.6. Results

3.6.1 Basic specifications

In this subsection, I discuss the results of estimating the probit model of entry into self-employment that I described in Section 3.4. Although my proposed estimation strategy involves jointly estimating models of asset levels and self-employment entry, I begin the discussion by considering a naïve, single-equation probit of self-employment entry that treats all covariates as exogenous. Table 3.6 presents the estimated coefficients

and marginal effects for the single-equation probit model. The marginal effects are evaluated at the sample means.

Specification 1 in Table 3.6 excludes my measure of absolute risk tolerance (γ). As discussed in Section 3.4, in this specification the estimated effect of assets (A) represents the sum of the direct effect due to liquidity constraints and the indirect effect due to the effect of A on γ. The estimates in Table 3.6 show that this "overall" effect is estimated to be 0.057 and is statistically significant at a 1% significance level. Evaluated at the sample mean of assets ($42,692), an increase in net assets of $100,000 is predicted to raise the self-employment entry probability by 0.0051, which is 11% of the average transition rate of 0.049 (Table 3.1). This small but statistically significant estimated effect of total net assets is consistent with what has been found in previous studies (Fairlie 2002; Hurst and Lusardi 2004).

My objective is to identify the separate effects of liquidity constraints and risk tolerance, so specification 2 in Table 3.6 presents estimates for my preferred specification in which both net assets and absolute risk tolerance are included in the probit model. In this specification, the estimated coefficient for net assets—which now identifies the direct effect of liquidity constraints on transitions into self-employment—becomes negative but is not significantly different from zero at conventional significance levels. However, the estimated effect of absolute risk tolerance proves to be positive, statistically significant at a 1% level, and economically quite important: the estimated marginal effect suggests that a 0.47 increase in an individual's level of risk tolerance (*i.e.,* an increase of one standard deviation) increases his probability of entering self-employment by 0.0073, or 15% of the unconditional transition rate. This estimated effect of γ is slightly larger than the "gross"

effect of A identified by specification 1. More importantly, the direct effect of A is now zero, so I conclude that an increase in net assets raises self-employment entry by raising individual risk tolerance level rather than by relaxing liquidity constraints. In other words, the "gross" effect of assets is entirely attributed to the indirect effect of assets on risk tolerance.

To account for the endogeneity of individual assets and absolute risk tolerance, I estimate the instrumental variables probit model discussed in Section 3.4. Before presenting those probit estimates, I briefly discuss the results of the equations for net assets; the estimates are presented in Table 3.7.[21] The table shows that the estimated coefficient for house price change (h) in the net assets equation is negative and statistically significant at a 1% significance level. This estimate suggests that the average individual in the sample does not own a house, presumably because the average age in the sample is only 30.5. Because an increase in local house prices raises the housing cost for the young and non-homeowners, it negatively affects the net assets of those "modal" sample members. By the same token, the estimated coefficients for the interactions between h and age and race show that an increase in local house prices is positively related to the net assets of white and older workers. This suggests that these individuals are more likely than their younger, nonwhite counterparts to own their home. The instruments are jointly significant at 1%, and the F-statistics presented in the bottom of Table 3.7 reveal that they satisfy the criterion of Staiger and Stock (1997) for weak instruments. To check overidentifying restrictions, I use the method of moments

[21] Table 3.7 contains ordinary least squares estimates of the assets equation so that the corresponding R^2 and F statistics can be assessed. The maximum likelihood estimates that I obtain by jointly estimating the assets equation and self-employment probit are virtually identical to what is seen in Table 3.7.

specification test by Newey (1985). The test statistic is obtained by regressing residuals from the second stage 2SLS equation of self-employment entry upon all exogenous variables in the system. The uncentered R^2 from this regression multiplied by the number of observations is the test statistic. Because the *p*-value of this statistic is 0.49, I conclude that the instrumental variables are exogenous.

Table 3.8 shows the estimates for the probit model that accounts for the endogeneity of both assets and risk tolerance. In specification 1, the estimated coefficient for net assets is positive but the value (0.029) is reduced to only half of the value seen in Table 3.6. In addition, it is not significantly different from zero. This suggests that unobserved factors that induce self-employment entry are positively related to personal asset level, thus causing the effect of assets obtained by naïve probit model to be overestimated. In specification 2 of Table 3.8, the estimated coefficient for net assets is negative but not significantly different from zero at any conventional significance level. However, the estimated coefficient for absolute risk tolerance in Table 3.8 is positive, significant at a 1% level, and identical in magnitude to the estimate in Table 3.6. These findings suggest that the absolute risk tolerance, which is correlated with level of net assets, is the key factor that is omitted from previous research on liquidity constraints. More to the point, liquidity constraints do not appear to be an important deterrent but the role of net assets on self-employment is changing individual risk preference rather than relaxing borrowing constraints. This confirms the importance of individual risk preference in influencing the self-employment entry decision.

To get a better sense of the effect of risk tolerance on the probability of entering self-employment, in Table 3.9 I present the computed probabilities of entering self-

employment (based on the estimates in Table 3.8) for a representative individual, after assigning him different values of absolute risk tolerance. The individual is assigned zero values for all dummy variables and the sample mean for all continuous variables (except γ). Thus, he is a 30 year old, never-married, nonunionized, nonblack, non-Hispanic man with 12 years of schooling who works 43 hours per week on a job he has held for 3.8 years. If this man has a level of absolute risk tolerance equal to the sample mean of 0.20, his predicted probability of entering self-employment in the next two years is 0.0493, which is very close to the unconditional 4.9% two-year transition rate seen in this sample. If his level of risk tolerance places him in the 25^{th} percentile of the distribution, his predicted probability is only 0.0460, but if his risk tolerance places him in the 95^{th} percentile this predicted probability increases 35% to 0.0619. Stated differently, this highly risk tolerant individual is 26% more likely than a man with "average" risk tolerance to enter self-employment. These estimates indicate that individual risk tolerance plays a very important role in determining which workers make a transition into self-employment.

Before proceeding to check the robustness of the results, I briefly consider how some of the variables other than A and γ are predicted to affect the self-employment decision. The estimated effects of demographic variables included in the model are not sensitive to whether risk tolerance is excluded or included. Workers are less likely to enter self-employment as they age although the estimated coefficient for age is not significantly different from zero. This is mainly due to the fact that the analysis focuses on the first transition into self-employment. In addition, nonblack/non-Hispanic workers, and workers with less than 12 years of schooling or workers with some college education

are more likely to enter into self-employment than are other workers. The non-monotonic relationship between education and self-employment is also found in other previous studies (Fairlie 2002, Francis and Demirap 2006). Among the current job characteristics that are included in the model, tenure with the current employer is found to be negatively related to self-employment entry. This may reflect the fact that firm-specific human capital or having a "good match" raises the cost of making the transition into self-employment. In addition, I find that workers who are in unions and those who are working in the government sector are less likely to enter into self-employment than are nonunion, nongovernment workers.

The estimates in Table 3.8 also imply that favorable economic conditions encourage self-employment entry. A one percentage point decrease in the local unemployment rate raises the probability of self-employment entry by 0.002, and this estimate is significant at a 1% level. In addition, state per capita income is positively related to self-employment entry although the estimated coefficient for this variable is not statistically significant.

Among the remaining person-specific variables included in the model, health limitations are found to have positive effects on entry into self-employment. The positive relationship between health limitations and self-employment entry suggests that the potential flexibility of one's work schedule may raise the value of self-employment for those who have health limitations. In addition, limited job availability due to health conditions may be a factor in pushing these workers into self-employment.

3.6.2 Robustness checks

I have established that an individual's level of absolute risk tolerance has a substantial effect on his predicted probability of entering self-employment, while his asset level has no effect. My extension of the Hurst and Lusardi (2004) instrumental variables proved to be unnecessary in light of my finding that the estimated (zero) effect of assets is invariant to the use of instruments, once individual heterogeneity in risk tolerance is taken into account. However, it remains to be seen how my other innovations (correcting self-reported risk tolerance for both measurement error and age variation, controlling for absolute risk tolerance rather than relative risk tolerance, and using a direct measure of risk tolerance rather than an indirect measure) affect the estimates. In this subsection, I present the results of a number of experiments that are designed to reveal whether the measure of risk tolerance "matters."

To conduct this sensitivity analysis, I estimate both the single equation probit and the IV probit using alternative measures or risk tolerance. Table 3.10 presents the estimated marginal effects of the key variables for each specification. For comparison, the first two columns of Table 3.10 repeat the marginal effects shown in Table 3.6 and Table 3.8. To obtain the estimates shown in column 3, I use a measure of absolute risk tolerance (γ_{93}) based on each individual's 1993 response; this measure of absolute risk tolerance does not correct for measurement error or age variation in self-reports.[22] To obtain the column 4 estimates, I use two reports of risk tolerance for each sample member and correct for measurement error but assume that individual risk tolerance does not

[22]The goal is to use a single response for each person rather than the 1993 response *per se*, so for 69 men who did not answer the risk questions in 1993, I use their 2002 responses instead.

change with age. In specification 5, I replace my absolute risk tolerance variable with a measure of *relative* risk tolerance (ρ) that is independent of asset levels. Although my measure of relative risk tolerance is the reciprocal of relative risk aversion and explicitly corrects for reporting errors (using two responses per individual), this specification is comparable to the one used by Kan and Tsai (2006). To obtain the estimates shown in column 6, I augment the column 2 specification by adding a dummy variable indicating whether the respondent sold illegal drugs more than six times in 1980. Fairlie (2002) argues that this measure of self-reported drug dealing controls for individual risk preference, entrepreneurial ability and/or a preference for autonomy.

When I assume all variables are exogenous (panel A of Table 3.10), the estimated marginal effect of assets is statistically indistinguishable from zero in every column except 1 and 5; when I use instrumental variables to account for the potential endogeneity of assets, the estimated effect of assets is always statistically insignificant. These results support my argument that it is necessary to include a measure of *absolute* risk tolerance in order to correctly identify the (zero) effect of assets on the probability of entering self-employment. Failing to control for risk tolerance (column 1) or controlling for *relative* risk tolerance (column 5) leads to the erroneous conclusion that liquidity constraints form a deterrent to self-employment—although as the panel B estimates indicate, this spurious result can always be eliminated via the use of instrumental variables.

Focusing on the panel A estimates, the estimated marginal effect of absolute risk tolerance in column 3 is only 0.002, which is 87% smaller than the estimate of 0.016 seen in column 2. This comparison reveals that the estimated effect of risk tolerance using a one-time measure of risk preference suffers from attenuation bias due to measurement

error. The estimated marginal effect of absolute risk tolerance in column 4 is 0.019, which is slightly larger but not significantly different than the preferred estimate shown in column 2. Clearly, accounting for age variation in self-reported risk tolerance has a trivial effect on the estimates (perhaps because I focus on first transitions into self-employment, thereby eliminating much of the age variation in the overall population of self-employed workers), but accounting for measurement error has a dramatic effect.

Interestingly, when I add the indirect "drug dealing" measure of risk tolerance suggested by Fairlie (2002) to the model (column 6), the estimated effects of assets and risk tolerance are unchanged from the column 2 estimates. However, drug dealing proves to have a positive and significant independent marginal effect (0.020) on the predicted probability of entering self-employment. Fairlie (2002) suggests that this variable may capture individual heterogeneity in risk aversion, entrepreneurial skill, and/or tastes for autonomy. The fact that its inclusion does not alter the estimated marginal effect of absolute risk tolerance indicates that it does *not* measure risk tolerance, but the size and precision of its estimated effect suggests that it serves as a proxy for other individual traits that are important determinants of the decision to enter self-employment.

3.7 Conclusion

In this paper, I identify the effects of individual risk tolerance and liquidity constraints on the probability that a young man enters self-employment. To construct a measure of relative risk tolerance, I use responses to "income gamble" questions asked in two years of the NLSY79, and I use this within-person variation to account for both survey response error and age variation in these self-reports. I then construct a measure of

absolute risk tolerance by assuming constant relative risk aversion, which implies that absolute risk tolerance increases with assets.

My estimates indicate that net assets have no significant effect on the probability of entering self-employment. I obtain this "zero effect" of assets three different ways: by omitting a measure of risk tolerance from the model and using instrumental variables to account for the endogeneity of assets (ala Hurst and Lusardi 2004), by controlling for relative risk tolerance and using the IV strategy, or simply by including a measure of *absolute* risk tolerance in the model; the inclusion of absolute risk tolerance eliminates the effects of net assets regardless of whether I use instruments. These results suggest that the failure to control for individual heterogeneity in absolute risk tolerance—which is positively correlated with personal asset levels—is why previous research found liquidity constraints to be an important deterrent to self-employment.

My estimates also reveal that absolute risk tolerance has a large, positive, and statistically significant effect on the probability of entering self-employment. An individual whose level of risk tolerance is one standard deviation above the mean is 15% more likely to enter self-employment than is an otherwise identical individual whose risk tolerance equals the sample mean. However, the estimated effect of risk preference on self-employment entry is attenuated by 87% when I fail to account for measurement error in self-reported risk tolerance. This evidence implies that the "income gamble" questions used in the NLSY79 and other surveys elicit valuable information on individual risk tolerance, but that it is crucially important to collect multiple responses and to correct them for reporting error.

In summary, I conclude that individual risk tolerance is an important determinant of entry into self-employment entry, and that net asset levels are only important insofar as they change individuals' risk tolerance; liquidity constraints do not play a significant role in deterring entry into self-employment. This latter result corroborates a recent finding of Hurst and Lusardi (2004), who refute the importance of liquidity constraints in the formation of small firms.

The fact that risk tolerance proves to be empirically important is consistent with an absence of markets to insure against losses from business failures. Because individuals cannot insure against this risk, they must be risk tolerant in order to enter self-employment. The fact that liquidity constraints prove to be empirically unimportant suggests that inefficient financial market do not hinder the decision to enter self-employment. If self-employment and business formation are considered desirable from an individual or social standpoint, policy makers need not worry about the lack of credit serving as a barrier to entry. However, there may be legitimate policy concerns regarding insurance market against the income risk born by the self-employed.

	Number	Percent
Transitions		
Wage to wage	26,309	95.1
Wage to self-employment	1,341	4.9
All	27,650	100.0
Individuals		
Never become self-employed	2,844	75.3
Become self-employed	931	24.7
All	3,775	100.0

Table 3.1: Number of transitions to self-employment and number of "ever self-employed" individuals

Response[a]	1993	2002	2002, by 1993 response			
			R1	R2	R3	R4
1	43.2	53.2	64.7	48.6	47.2	41.6
2	10.9	10.2	8.3	15.3	13.1	9.3
3	17.4	16.7	12.9	17.1	22.5	18.6
4	28.5	19.9	14.1	19.1	17.2	30.4
No. of men	3,706	3,184	1,344	346	551	874

[a]1: reject both one-third and one-fifth (least risk tolerant)
2: reject one-third but accept one-fifth
3: accept one-third but reject one-half
4: accept both one-third and one-half (most risk tolerant)

Note: The three samples consist of 3,706 men who answered risk questions in 1993, 3,184 men who answered them in 2002, and 3,115 men who answered them in both years.

Table 3.2: Distribution of risk tolerance categories reported in 1993 and 2002

Response[a]	Lower bound	Upper bound
1	0	0.27
2	0.27	0.50
3	0.50	1.00
4	1.00	∞

[a]1: reject both one-third and one-fifth (least risk tolerant)
2: reject one-third but accept one-fifth
3: accept one-third but reject one-half
4: accept both one-third and one-half (most risk tolerant)

Table 3.3: Lower and upper bounds of risk tolerance computed for each categorical response

Parameter	Estimates
μ	0.177
	(0.109)
σ_δ	0.900**
	(0.029)
σ_υ	1.529**
	(0.024)
β	-0.042**
	(0.003)
λ	0.257**
	(0.015)
Log likelihood	-20,210

Note: Standard errors are in parentheses; λ is the share of total variance due to individual effects (δ).
* Significant at 5%; ** Significant at 1%

Table 3.4: Maximum likelihood estimates of risk tolerance function

Variable	Definition	Mean	Std. Dev.
γ	Absolute risk tolerance	.20	.47
A	Net assets[a]	.43	.86
Age and race (*X*)			
Age	Age (years)	30.50	4.87
Hispanic	1 if Hispanic	.19	
Black	1 if black	.29	
Other variables (*Z*)			
S11	1 if highest grade completed < 12	.14	
S13	1 if highest grade completed = 13-15	.21	
S16	1 if highest grade completed ≥ 16	.19	
Married	1 if married	.51	
Divorced	1 if divorced or separated	.11	
Num. kids	Number of children under age 18	.84	1.13
Wage	Hourly wage multiplied by 2,000 hours[a]	.43	10.83
Hours	Average hours worked per week	43.00	9.78
Tenure	Tenure with current employer (years)	3.79	3.88
New job	1 if tenure < 1	.29	
Union	1 if union job	.21	
Government	1 if government job	.13	
Unemp. rate	Local unemployment rate	6.56	2.78
Urban	1 if reside in urban area	.80	
Northeast	1 if reside in northeast	.17	
North central	1 if reside in north central	.24	
West	1 if reside in west	.20	
State Income	Gross personal income per capita in state[a]	.27	.04
AFQT	Percentile score on Armed Forces Qualif. Test	41.38	29.27
Health	1 if health limits ability to work	.03	
No. obsns.		27,650	

[a]In hundreds of thousands of CPI-U-deflated dollars, using 2002 as the base year.

Note: The model also includes 10 industry dummies, a dummy variable indicating year before 1990, and 4 dummy variables indicating that industry, union, AFQT, and health are missing

Table 3.5: Summary statistics for selected variables used in the transition model

	(1)		(2)	
Variables	Coefficients	Marginal effects	Coefficients	Marginal effects
A (Net assets)	0.057 [0.017]**	0.005 [0.002]**	-0.042 [0.032]	-0.004 [0.003]
γ (Abs. risk tol.)			0.175 [0.046]**	0.016 [0.004]**
Age	-0.018 [0.006]**	-0.002 [0.001]**	-0.016 [0.006]**	-0.002 [0.001]**
Hispanic	-0.060 [0.053]	-0.005 [0.005]	-0.060 [0.053]	-0.005 [0.005]
Black	-0.060 [0.048]	-0.005 [0.0043]	-0.060 [0.048]	-0.005 [0.004]
S11	0.085 [0.051]+	0.008 [0.005]+	0.083 [0.051]	0.007 [0.005]
S13	0.052 [0.047]	0.005 [0.004]	0.049 [0.047]	0.004 [0.004]
S16	-0.007 [0.058]	-0.001 [0.005]	-0.005 [0.058]	0.000 [0.005]
Married	0.050 [0.043]	0.005 [0.004]	0.054 [0.043]	0.005 [0.004]
Divorced	0.146 [0.054]**	0.013 [0.005]**	0.144 [0.054]**	0.013 [0.005]**
Number of kids	0.010 [0.019]	0.001 [0.002]	0.012 [0.019]	0.001 [0.002]
Wage	-0.007 [0.015]	-0.001 [0.001]	-0.007 [0.015]	-0.001 [0.001]
Hours	0.003 [0.002]	0.000 [0.000]	0.003 [0.002]	0.000 [0.000]
New job	0.072 [0.036]*	0.006 [0.003]*	0.077 [0.036]*	0.007 [0.003]*
Tenure	-0.035 [0.007]**	-0.003 [0.001]**	-0.034 [0.007]**	-0.003 [0.001]**
Union	-0.138 [0.042]**	-0.012 [0.004]**	-0.136 [0.042]**	-0.012 [0.004]**
Government	-0.126 [0.068]+	-0.011 [0.006]+	-0.129 [0.068]+	-0.012 [0.006]+
Unemp. rate	-0.021 [0.007]**	-0.002 [0.001]**	-0.021 [0.007]**	-0.002 [0.001]**
Urban	0.060 [0.044]	0.005 [0.004]	0.057 [0.044]	0.005 [0.004]
Northeast	-0.032 [0.063]	-0.003 [0.006]	-0.034 [0.063]	-0.003 [0.006]
North central	-0.016 [0.047]	-0.001 [0.004]	-0.016 [0.047]	-0.001 [0.004]
West	-0.006 [0.054]	-0.001 [0.005]	-0.010 [0.054]	-0.001 [0.005]
State income	0.671 [0.592]	0.060 [0.053]	0.717 [0.592]	0.064 [0.053]
AFQT	0.000 [0.001]	0.000 [0.000]	0.000 [0.001]	0.000 [0.000]
Health	0.324 [0.075]**	0.029 [0.007]**	0.324 [0.076]**	0.029 [0.007]**
Constant	-1.285 [0.250]**		-1.348 [0.251]**	
Log likelihood	-5127.6663		-5119.4104	

Note: Marginal effects are evaluated at the sample means. The model also includes 10 industry dummies, a dummy variable indicating year before 1990, and 4 "missing variable" dummies (see Section 3.5). Robust standard errors adjusted for correlation within individual are in brackets.
+ Significant at 10% * Significant at 5% ** Significant at 1%

Table 3.6: Probit estimates of the probability of entering self-employment
(All covariates assumed exogenous)

Variables	A (Net assets)
h (House price change)	-0.035 [0.007]**
*h**Age	0.001 [0.000]**
*h**Hispanic	-0.008 [0.002]**
*h**Black	-0.011 [0.002]**
Age	0.021 [0.003]**
Hispanic	-0.060 [0.028]*
Black	-0.125 [0.024]**
S11	-0.090 [0.017]**
S13	0.085 [0.024]**
S16	0.341 [0.034]**
Married	0.226 [0.019]**
Divorced	-0.027 [0.018]
Number of kids	0.002 [0.009]
Wage	0.000 [0.000]
Hours	0.005 [0.001]**
New job	0.068 [0.014]**
Tenure	0.036 [0.003]**
Union	0.015 [0.019]
Government	-0.126 [0.029]**
Unemployment rate	-0.011 [0.003]**
Urban	-0.038 [0.019]*
Northeast	0.045 [0.032]
North central	-0.056 [0.022]*
West	0.024 [0.027]
State income	1.364 [0.321]**
AFQT	0.002 [0.001]**
Health	0.029 [0.038]
Constant	-1.100 [0.132]**
R-squared	0.22
F-test : all variables = zero	35.7
F-test : instruments = zero	11.1

Note: Marginal effects are evaluated at the sample means. The model also includes 10 industry dummies, a dummy variable indicating year before 1990, and 4 "missing variable" dummies (see Section 3.5). Robust standard errors adjusted for correlation within individual are in brackets.
+ Significant at 10% * Significant at 5% ** Significant at 1%

Table 3.7: Estimated coefficients for the model of net assets

	(1)		(2)	
Variables	Coefficients	Marginal effects	Coefficients	Marginal effects
A (Net assets)	0.029 [0.376]	0.003 [0.033]	-0.025 [0.378]	-0.002 [0.034]
γ (Abs. risk tol.)			0.175 [0.046]**	0.016 [0.004]**
Age	-0.017 [0.013]	-0.002 [0.001]	-0.017 [0.013]	-0.002 [0.001]
Hispanic	-0.062 [0.066]	-0.006 [0.006]	-0.058 [0.067]	-0.005 [0.006]
Black	-0.066 [0.086]	-0.006 [0.008]	-0.056 [0.087]	-0.005 [0.008]
S11	0.082 [0.062]	0.007 [0.005]	0.085 [0.061]	0.008 [0.006]
S13	0.055 [0.058]	0.005 [0.005]	0.048 [0.058]	0.004 [0.005]
S16	0.003 [0.141]	0.000 [0.013]	-0.011 [0.141]	-0.001 [0.013]
Married	0.057 [0.095]	0.005 [0.009]	0.050 [0.095]	0.004 [0.008]
Divorced	0.146 [0.056]**	0.013 [0.005]**	0.145 [0.056]**	0.013 [0.005]**
Number of kids	0.010 [0.019]	0.001 [0.002]	0.012 [0.019]	0.001 [0.002]
Wage	-0.007 [0.015]	-0.001 [0.001]	-0.007 [0.015]	-0.001 [0.001]
Hours	0.003 [0.003]	0.000 [0.000]	0.002 [0.003]	0.000 [0.000]
New job	0.074 [0.045]+	0.007 [0.004]+	0.076 [0.045]+	0.007 [0.004]+
Tenure	-0.034 [0.015]*	-0.003 [0.001]*	-0.035 [0.015]*	-0.003 [0.001]*
Union	-0.137 [0.043]**	-0.012 [0.004]**	-0.136 [0.043]**	-0.012 [0.004]**
Government	-0.130 [0.082]	-0.012 [0.007]	-0.127 [0.083]	-0.011 [0.007]
Unemp. rate	-0.021 [0.008]**	-0.002 [0.001]**	-0.020 [0.008]*	-0.002 [0.001]*
Urban	0.059 [0.047]	0.005 [0.004]	0.058 [0.047]	0.005 [0.004]
Northeast	-0.031 [0.064]	-0.003 [0.006]	-0.034 [0.064]	-0.003 [0.006]
North central	-0.017 [0.051]	-0.002 [0.005]	-0.015 [0.051]	-0.001 [0.005]
West	-0.005 [0.055]	-0.001 [0.005]	-0.010 [0.055]	-0.001 [0.005]
State income	0.710 [0.806]	0.063 [0.073]	0.694 [0.811]	0.062 [0.072]
AFQT	0.000 [0.001]	0.000 [0.000]	0.000 [0.001]	0.000 [0.000]
Health	0.325 [0.076]**	0.029 [0.007]**	0.324 [0.076]**	0.029 [0.007]**
Constant	-1.324 [0.574]*		-1.324 [0.587]*	
Log likelihood	-36556.3510		-36548.0970	

Note: Marginal effects are evaluated at the sample means. The model also includes 10 industry dummies, a dummy variable indicating year before 1990, and 4 "missing variable" dummies (see Section 3.5). Robust standard errors adjusted for correlation within individual are in brackets.
+ Significant at 10% * Significant at 5% ** Significant at 1%

Table 3.8: IV/Probit estimates of the probability of entering self-employment
(Net assets and absolute risk tolerance assumed endogenous)

Level of risk tolerance (percentile)	Predicted Probability
25	0.0460
50	0.0468
75	0.0493
90	0.0549
95	0.0619
Mean	0.0493

Note: Probabilities are computed for an individual with all continuous variables equal to the sample mean and all dummy variables equal to zero.

Table 3.9: Predicted probability of entering self-employment by level of absolute risk tolerance (Based on estimates in table 3.8)

Panel A: Probit

	(1)	(2)	(3)	(4)	(5)	(6)
A (Net assets)	0.005 [0.002]**	-0.004 [0.003]	0.002 [0.002]	-0.003 [0.003]	0.005 [0.002]**	-0.004 [0.003]
γ (Absolute risk tolerance)		0.016 [0.004]**				0.015 [0.004]**
γ_{93} (1993 report only)			0.002 [0.001]**			
γ_{ME} (corrected for ME only)				0.019 [0.006]**		
ρ (Relative risk tolerance)					0.017 [0.005]**	
Former drug dealing						0.020 [0.006]**

Panel B: IV/Probit

	(1)	(2)	(3)	(4)	(5)	(6)
A (Net assets)	0.003 [0.033]	-0.002 [0.034]	0.000 [0.033]	-0.006 [0.034]	0.003 [0.033]	-0.001 [0.033]
γ (Absolute risk tolerance)		0.016 [0.004]**				0.015 [0.004]**
γ_{93} (1993 report only)			0.002 [0.001]**			
γ_{ME} (corrected for ME only)				0.019 [0.006]**		
ρ (Relative risk tolerance)					0.017 [0.005]**	
Former drug dealing						0.020 [0.007]**

Note: Marginal effects are evaluated at the sample means. Estimates in columns (1) and (2) are from Tables 3.6 and 3.8. The model also includes all other covariates used in the previous specification (see section 3.5). Robust standard errors adjusted for correlation within individual are in brackets.

+ Significant at 10% * Significant at 5% ** Significant at 1%

Table 3.10: Marginal effects based on Probit and IV/Probit estimates using alternative measures of risk tolerance

CHAPTER 4

RACIAL DIFFERENCES IN SELF-EMPLOYMENT EXITS

4.1 Introduction

The self-employment rate of minority workers is significantly lower than that of white workers. According to statistics from the 2003 Current Population Survey (CPS), 14.5% of white, male workers are self-employed, versus only 7.5% of blacks and 8.4% of Hispanics (Hipple 2004). The relative lack of businesses owned by minorities, and by blacks in particular, is a concern for policy makers and researchers. Because self-employment is often regarded as a way for disadvantaged workers to achieve economic prosperity and upward mobility (Fairlie 2004), researchers have sought to understand what contributes to these racial differences in cross-sectional self-employment rates (see, for example, Fairlie 1999; Hout and Rosen 2000; Lofstrom and Wang 2006).

In this paper, I use data from the 1979 National Longitudinal Survey of Youth (NLSY79) to examine the employment patterns of an "age uniform" sample of black, white, and Hispanic men, all of whom are observed from age 22 to age 40. I find that racial differences in "ever self-employed" during this period are small, while racial differences in the "point in time" self-employment rate mimic those seen in the CPS. This comparison demonstrates that the cross-sectional self-employment rate shows such large racial differences not because minorities fail to enter self-employment, but because their self-employment spells are relatively short-lived. Moreover, I find that high rates of self-

employment to *nonemployment* transitions among minorities account for much of the racial differences in self-employment exits. The fact that self-employed minorities are likely to end up nonemployed is noteworthy because it suggests that providing minority workers with self-employment opportunities does not necessarily give them a route into employment stability.

In light of these patterns seen in the NLSY79, I estimate a model of self-employment exits that (a) distinguishes between transitions to wage employment (*i.e.*, nonself-employment) and nonemployment; (b) includes employment histories as wells as education, family background, and financial status among the covariates; and (c) allows selected parameters to vary across racial/ethnic groups. Previous studies of self-employment durations have examined the importance of education (Bates 1990), financial capital (Holtz-Eakin, Joulafaian, and Rosen 1994), and individual work experience (Taylor 1999; van Praag 2003), but only Fairlie (1999, 2006), Fairlie and Robb (2007) and Lofstrom and Wang (2006) have considered racial differences in self-employment exit decisions. However, the literature has yet to assess racial differences in the different types of exits from self-employment. Distinguishing transitions to nonemployment from transitions to nonself-employment is important because moves to new "wage jobs" do not necessarily imply business failure, but may reflect situations where self-employment afforded the individual better earnings opportunities.

Estimates from my multinomial logit model of self-employment exits reveal that weak attachment to the labor market raises the probability of a self-employment to nonemployment transition, while lack of industry-specific and self-employment experience is associated with a higher predicted probability of moving into wage

employment. In short, lack of prior work experience by minority workers, and by blacks in particular, significantly contributes to the racial gap in self-employment exit rates. Assigning blacks and Hispanics the mean value among whites of each work history variable—prior nonemployment, industry-specific, and self-employment experience—reduces the predicted black-white gap in the first-year self-employment survival rate by 34% and the Hispanic-white gap by 15%. This combined contribution of employment experiences to racial gaps in predicted self-employment survival rates is larger than the combined contribution of schooling, parental schooling, and total assets, which are often considered to be key determinants of self-employment decisions.

4.2 Background

Research on self-employment has grown rapidly in recent years. One strand of the literature focuses on factors that affect entry into self-employment. Studies have shown that workers tend to enter self-employment when they have available credit (Blanchflower and Oswald 1998; Dunn and Holtz-Eakin 2000; Evans and Jovanovic 1989), when they have high tolerance for risk (Ahn 2007; Fairlie 2002; Kihlstrom and Laffont 1979), and when financial capital and entrepreneurial skills have been transferred to them across generations or within family (Bruce 1999; Dunn and Holtz-Eakin 2000). In the female labor supply literature, research has examined the role of self-employment as a means for women to carry out both household work and wage work (Hundley 2000; Taniguchi 2002).

Another group of studies examines the decision to *exit* from self-employment. Many of the same factors that affect entry into self-employment have been found to be

important determinants of subsequent exits. In particular, education (Bates 1990) and assets, as measured by inheritance and interest income (Holtz-Eakin *et al.* 1994, Taylor 1999), prove to be positively associated with self-employment duration. In addition, various components of prior work experience are key determinants. Taylor (1999) shows that previous self-employment experience reduces the probability of a voluntary exit from self-employment, while van Praag (2003) shows that previous experience in the same occupation or industry plays a similar role; both these authors find that prior unemployment experience is associated with a higher probability of an involuntary exit. These results—which I draw on for the specification of my self-employment exit model—suggest that "positive" work experience that augments entrepreneurial and/or industry-specific skill promotes business survival, while "negative" (unemployment) experience is associated with subsequent business failure.

My analysis also builds on the subset of the literature that seeks to identify determinants of racial and ethnic differences in self-employment entry and exit. Prior research has shown that relatively low rates of parental self-employment, low levels of wealth, and low schooling levels are important contributors to the low self-employment rates of black workers (Fairlie 1999, 2006; Hout and Rosen 2000; Lofstrom and Wang 2006). In a recent study, Fairlie and Robb (2007) argue that the well-established effects of family background on self-employment outcomes operate via the acquisition of business experience. They find that black business owners are about half as likely as their white counterparts to have worked in family members' businesses. In addition, they demonstrate (using data from the 1992 Characteristics of Business Owners survey) that

having work experience in a family member's business explains between 6% and 12% of the racial difference in such outcomes as profits, sales and business closure.

The small number of studies that specifically examine racial differences in self-employment exits are particularly relevant to my analysis. While Fairlie (1999, 2006) and Lofstrom and Wang (2006) find that education, family background and financial factors are important determinants of self-employment entry, they are unable to pinpoint the key contributors to racial differences in subsequent exit rates. In addition, they do not distinguish between different "types" of self-employment exits; that is, transitions to nonemployment versus transitions to wage (or "nonself") employment. This distinction is likely to be important, for a transition into wage employment does not necessarily imply business failure but may instead represent a "positive" movement to a better earnings opportunity. Moreover, the existing literature does not assess the link between work histories and racial/ethnic differences in self-employment exits. As has been well-documented outside the self-employment literature, unemployment rates of black men are typically more than twice as high as those of white men (Stratton 1993; Fairlie and Sundstrom 1999) and weak attachment to the labor market in the early career by black men explains much of the black-white gap in wage levels (D'Amico and Maxwell 1994).

Given the aforementioned finding that previous work experiences are found to be significant determinants of self-employment exit decisions, it is worth asking how much of the *racial* difference in exit rates is attributable to these factors. An investigation of the link between employment histories and self-employment survival also contributes to the general job mobility literature that examines the effects of early employment stability on future labor market outcomes such as wages/compensation (Gardecki and Neukmark

1998; Neumark 2002) and transitions into full-time employment (Klerman and Karoly 1994; Gardecki and Neukmark 1998).

4.3 Model of exit from self-employment

I model self-employment exits by assuming that each year, self-employed individuals must decide whether to remain self-employed (SE), move to wage employment (WE), or move to nonemployment (NE). Each worker simply chooses the state that is associated with the highest expected utility; those individuals who decide to remain self-employed repeat the decision every period until a transition is made.

I assume that the state-specific, expected utility of self-employed workers can be approximated by the following linear function:

$$y_{it}^{m} = X_i \beta^{m} + Z_{it} \delta^{m} + u_{it},$$

where m represents each state (SE, WE, NE) in the opportunity set of worker i at time t. The vector X_i contains measures of the individual's employment history: time spent in nonemployment, industry-specific experience, prior self-employment and age, all of which are measured at the start of the current self-employment spell. Prior nonemployment experience is likely to lower the value of both self-employment and wage employment because previous joblessness keeps the worker from accumulating labor market skill; this factor should therefore raise the likelihood of SE-to-NE transitions. Past experience in the same industry should raise the relative value of both self-employment and wage employment in the same industry if the worker has gained industry-specific human capital. Similarly, I expect previous self-employment experience to raise the value of self-employment relative to the other options, given that the worker

is likely to have accumulated valuable entrepreneurial skill. Thus, workers with industry experience and prior self-employment experience are less likely than others to exit self-employment.

The vector Z_{it} represents personal background factors that affect the expected utility of each state, including schooling, father's schooling, and financial status. I include race/ethnicity dummies that allow the intercepts of each utility function to vary across worker "type," and I interact selected components of X_i and Z_{it} with the race/ethnicity dummies. This additional flexibility allows the marginal effect of a given factor on a given state's expected value to itself be a function of race/ethnicity.

I assume that u_{it}, which represents unobserved factors, is drawn from an extreme value distribution. While it is implausible to assume that the components of X_i are independent of the unobservables, I partially address this endogeneity problem by conditioning on many characteristics (Z_{it}) that "explain" early-career employment decisions. However, this study is best viewed as a descriptive examination of the noncausal relationships between work histories and self-employment exit probabilities. In addition to the potential endogeneity issue, I acknowledge that the unobserved factors are correlated over time for a given individual. To obtain correct standard error for statistical inference, I use sandwich-type, Huber-White standard errors that account for this within-person nonindependence of u_{it}.

4.4 Data

4.4.1 Sample selection

The data used in this study are from the 1979 National Longitudinal Survey of Youth (NLSY79), which began in 1979 with a nationally representative sample of 12,686 individuals who were ages 14 to 22. The original sample consists of three subsamples: a sample of 6,111 individuals representing the civilian population, a supplemental sample of 5,295 black, Hispanic and economically disadvantaged non-Hispanic, non-black ("white") youth, and a military sample of 1,280 individuals who enlisted in the armed forces as of September 1978. These respondents were interviewed annually from 1979 to 1994 and biennially thereafter. I use data from each interview from 1979 through 2004.

In investigating the longitudinal self-employment patterns of NLSY79 respondents, I choose to follow sample members over a fixed portion of the life-cycle. Following sample members over a fixed period ensures that any racial differences that I uncover are "real" and not due to, say, blacks being observed at younger ages than whites due to differential attrition rates. I confine my sample to workers who are observed for 19 years of their careers, starting at age 22. I use age 22 to initialize my "age uniform" sample because all respondents are at least 22 years old when first interviewed in 1979 (*i.e.,* all birth years are observed from age 22 onward). I choose age 40 as my cutoff because relatively few respondents are observed beyond age 40 due to sample attrition, plus the fact that the age range of the original sample is only 39 to 47 in 2004.

In constructing my "age uniform" sample, I begin by including only male respondents (who account for 6,403 of the original 12,686 survey respondents) because self-employment decisions of women differ from those of men in various dimensions

(Hundley 2000, Taniguchi 2002). Second, I drop 2,300 individuals who left the survey before reaching age 40. Third, I eliminate 67 men who did not report any job lasting at least 16 weeks on which he worked at least 30 hours per week. The final sample includes 4,036 men; 2,045 (51%) are white, 1,214 (30%) are black, and 777 (19%) are Hispanic.

As discussed further in section 4.5, 1,335 of my sample members become self-employed and this subsample is observed holding 2,113 self-employment jobs between ages 22 and 40. In order to model transitions from self-employment to either wage jobs or nonemployment, I construct a sample of 7,168 person-year observations for the 2,113 self-employment jobs held by these 1,335 men. In constructing yearly observations, I define a "transition" to (continuing) self-employment (SE) if the individual remains self-employed at t+1. I consider that he makes a transition from self-employment to wage-employment (WE) if he ends his self-employment spell by t+1 and starts a nonself-employed job within four weeks of leaving self-employment. In the remaining cases where the worker leaves self-employment by t+1, I classify him as leaving self-employment for nonemployment (NE).

4.4.2 Definition of self-employment

I classify a job as "self-employment" if the worker reports himself to be working for profit or fees in his own business, shop, office, or farm; such jobs are identified from answers to "class of worker" questions asked in every survey round.[23] All jobs not classified as self-employment, including those where the respondents report themselves

[23] From 2002 onward, in addition to the class of worker question, respondents were also asked a series of questions that determine the type of job (traditional, non-traditional, or self-employed). To maintain comparability across years, I ignore this additional information and use the "class of worker" definition of self-employment for all years.

to be working without pay in a family business or farm, are classified as "wage employment." Class of worker information is available for up to five jobs that respondents report each year. In some cases, this information is missing because the question was not asked for jobs on which workers "usually" work less than ten hours a week and for jobs held less than nine weeks since the last interview. In other cases, respondents were asked to report their "class of worker" but valid information was not obtained because they refused to give job information or reported that they did not know. I impute self-employment status using information from other years if the respondent reported "class of worker" information for the same job in an adjacent interview.[24]

4.4.3 Covariates

The top rows of Table 4.1 contain sample transition rates for the 7,168 person-year observations used to model exits from self-employment. The data reveal that white men have a year-to-year survival (SE-to-SE) rate of 81%, which is about seven percentage points higher than the rates seen for blacks and Hispanics. These racial differences are almost entirely due to the fact that blacks and Hispanics are much more likely than whites to leave self-employment for nonemployment: roughly 11% of observations correspond to a transition into nonemployment for members of both minority groups, versus only 5% of observations for whites. At the same time, men in all three racial/ethnic groups have a 14-16% likelihood of their self-employment ending with a transition to wage employment in the next year. These summary statistics indicate that

[24] Class of worker information is missing for 12.6% (4,332) of the 34,251 jobs reported by my 4,036 sample members between ages 22 and 40. I am able to impute self-employment status for 487 of those missing cases; the remaining 3,845 jobs are dropped from the sample.

black and Hispanic men stay self-employed for shorter durations than do their white counterparts, and that they are more than twice as likely to make a transition from self-employment to nonemployment; I pursue these issues in Section 4.5.

In the rest of Table 4.1, I present summary statistics for the covariates used to model self-employment exits. The first three covariates measure previous labor market experience. I control for the percent of time spent in nonemployment, the percent of time spent in the same one-digit industry as the current (self-employment) job, and the percent of time spent in prior self-employment; all three work history variables are measured from the individual's 22nd birthday to the start of the current self-employment spell. In addition, I include age at the start of the spell. Table 4.1 shows that minority men, and blacks in particular, spend more time on average in nonemployment before the start of current self-employment than do whites (28% for blacks, 22% for Hispanics, and 16% for whites). Minorities also spend a lower percent of time, on average, working in the same industry (32% for blacks and 33% for Hispanics, versus 45% for whites) and in self-employment (15% for blacks, 21% for Hispanics, and 27% for whites).

The next set of variables summarized in Table 4.1 is intended to control further for workers' skill levels, family background, and financial status. I control for both the worker's highest graded completed and the highest graded completed by his father. Schooling attainment is expected to be positively related to the survival of self-employment if it represents human capital required for success in business (Bates 1990) or unmeasured access to funding opportunities. A high level of schooling may also raise the probability of a SE-to-WE transition if it increases the possibility of receiving an attractive wage offer (Taylor 1999). I include the highest grade completed of the worker's

father in order to proxy entrepreneurial ability and/or parental wealth, following Fairlie (1999). Unsurprisingly, Table 4.1 demonstrates that blacks and Hispanics have lower average schooling than whites, and are less likely to have fathers with high schooling levels. In order to control for the effects of liquidity on self-employment survival, I include the level of total net asset measured one year prior to the start of the job.[25]

As additional controls, I include a dummy variable indicating whether the worker was born outside U.S., marital status dummy variables (married, divorced/separated with never married the omitted category), and number of children in the household. I also include controls for environmental factors that potentially affect exit decisions: a measure of the unemployment rate in the worker's county of residence and a dummy variable indicating whether the worker lives in an urban area. In order to handle duration dependence of the exit decisions, I include five dummy variables that indicate years in the current self-employment job. Finally, I add 11 dummy variables indicating the industry of the self-employment job.

In contrast to the segmented sample used for Table 4.1, I pool race/ethnicity groups in estimating the multinomial logit model and include dummy variables indicating whether the worker is black or Hispanic. To allow the coefficients to differ by race/ethnicity, I interact the black and Hispanic indicators with selected covariates. In

[25]Detailed information on personal assets is only available from 1985 onward in the NLSY79. Thus, I impute net assets for the years before 1985 with predicted values based on a person-specific asset-year equation. The asset measure is deflated by the CPI-U and expressed in hundreds of thousands of 2002 dollars.

selecting the variables to be interacted, I first interact race dummies with all covariates and keep the interactions that are statistically significant.[26]

4.5 Summary of employment patterns

4.5.1 Self-employment rates

Table 4.2 summarizes the extent of self-employment observed among my 4,036 sample members between ages 22 and 40. While a third of all sample members experience self-employment by age 40, as expected blacks are less likely to experience self-employment than are Hispanics and whites: 28.7% of black men are "ever self-employed" compared to 36.5% of white men and 30.9% of Hispanic men. However, these racial/ethnic differences in rates of "ever self-employed" are much smaller than the differences in cross-sectional rates reported elsewhere. For example, the statistics reported in the introduction, based on Hipple's (2004) analysis of the CPS, suggest that white men are roughly twice as likely as black men to be self-employed (14.5% versus 7.5%), with the self-employment rate for Hispanic men lying in between (8.4%).

To determine whether the dramatic differences between the "ever self-employed" rates found in the NLSY79 and the CPS rates are due to differences in the observation period (a 19-year window versus a cross-section) or other factors, I construct cross-sectional self-employment rates for my sample members; *i.e.*, I use one observation per year per respondent for the 19-year observation period. In the second row of Table 4.2, I report these cross-sectional self-employment rates by race. They reveal that the self-

[26]Given that the work history variables are key to my analysis, I interact each of them with both race/ethnicity dummies regardless of the statistical significance of the estimated coefficients.

employment rate of black men (5.1%) is roughly half that of white men (9.5%), while the rate for Hispanics (6.5%) falls in the middle. These cross-sectional self-employment rates mimic the large racial differences reported by Hipple (2003). However, they are lower than Hipple's CPS-based rates, presumably because he uses men of all ages (16 and up) while I focus on men in their 20s and 30s. To confirm that the age composition of the two samples accounts for the remaining difference between my NLSY79 cross-sectional rates and Hipple's CPS rates, I calculate self-employment rates for the March 2004 CPS using a sample of 22-40 year old men. As Table 4.2 reveals, these age-adjusted CPS rates match the cross-sectional rates seen in the NLSY79

In summary, Table 4.2 reveals that "ever self-employed" rates are much higher than cross-sectional rates and show much less racial disparity. These results suggest that blacks, whites and Hispanics do not differ dramatically in their probability of entering self-employment, but that the self-employment spells of minorities are relatively short-lived. The remainder of this section is dedicated to exploring these racial/ethnic disparities in more detail.

4.5.2 Employment patterns of "ever self-employed" workers

In Table 4.3, I summarize the number of self-employment spells held by "ever self-employed" men during the 19-year window. Close to two-thirds of "ever self-employed" workers hold only one self-employment job while only 14% hold three or more self-employment jobs. While white and Hispanic men look virtually identical in this dimension, blacks who enter self-employment are more likely than their counterparts to hold only one such job: 71% of blacks have only a single self-employment spell, and

only 9.5% of blacks hold three or more self-employment jobs. Seen in isolation, Table 4.3 suggests that Hispanics and whites have similar self-employment patterns, and is consistent with the notion that blacks have the most stable self-employment experiences of the three groups. However, neither conclusion is supported by subsequent analysis.

Table 4.4 shows the distribution of self-employment durations for the three subgroups of "ever self-employed" men. The average self-employment job lasts only 36 months for blacks and 39 months for Hispanics, while whites remain self-employed, on average, for 51 months—more than one year longer than the typical minority worker.[27] More than one-third of self-employment jobs held by black and Hispanic men last for less than one year, while only 26% of white men's self-employment jobs are that short. In conjunction with the statistics presented in Table 4.3, it is clear that blacks tend to hold a single, short-lived self-employment job before moving onto another activity.

In panel A of Table 4.5, I show how the time spent self-employed during this 19-year window is distributed among workers. These distributions underscore the fact that minority workers are self-employed for a shorter period than are whites. For instance, 24% of whites are self-employed for more than half the observation window but only 10% of blacks and 13% of Hispanics experience a similar degree of self-employment continuity. At the other extreme, close to half the blacks and Hispanics in my sample spend less than 10% of the observation window in self-employment, versus only 32% of their white counterparts.

[27] For jobs that start before age 22, actual starting date is used. For jobs that end before the last interview, true duration is used. If the job is right-censored, the last interview date is used as the ending date.

Given that Hispanics and especially blacks tend to spend less time than whites in self-employment from age 22 to age 40, I now consider which employment status accounts for their remaining time. In panels B and C of Table 4.5, I summarize the distributions of time spent in wage employment (jobs not classified as self-employment) and nonemployment during the observation period. Unsurprisingly, minority workers tend to be nonemployed for a longer period than whites: 20% of blacks, 10% of Hispanics, and only 3% of whites are nonemployed for more than half the observation window, while the mean weeks spent nonemployed is 27 for blacks, 20 for Hispanics, and only 12 for whites. However, the racial/ethnic differences in the percentage of weeks spent wage-employed are relatively small. To illustrate, the difference in means between blacks and whites is less than four weeks (54.5 versus 58.2 weeks), while the difference in means is zero between Hispanic and white. These findings show that racial differences in time spent nonemployed account for much of the racial differences in time spent in self-employment.

4.6 Determinants of self-employment exits

In this section, I present estimates from the multinomial logit model of self-employment exits described in Section 4.3. My goal is to identify key determinants of the racial/ethnic gaps in each type of self-employment exit (SE to NE and SE to WE) and, of course, in self-employment survival rates (SE to SE). Specifically, I ask how much the racial/ethnic gaps in predicted transition probabilities will narrow if a typical black and typical Hispanic are assigned the same (mean) work histories observed for the typical white worker. I then ask how the estimated effects of work history variables compare to the

combined, estimated effects of schooling, parental schooling, and asset levels, which are considered to be key determinants of self-employment survival (Bates 1990; Holtz-Eakin *et al.* 1994). Because the logit estimates are difficult to interpret directly, I report the estimated parameters in Table 4.7 and focus instead on predicted probabilities based on those underlying estimates.

In Table 4.6, I compute the predicted probabilities of SE-to-NE, SE-to-WE, and SE-to-SE transitions for representative black, white, and Hispanic workers under a variety of alternative assumptions. I first compute baseline predicted probabilities for each racial/ethnic group by assuming that each representative individual is 30 years old, is in his first year of self-employment, and has characteristics equal to the race-specific mean for continuous variables and race-specific mode for each dummy variable. Under these baseline assumptions, a representative Hispanic (black) has a 0.155 (0.194) predicted probability of leaving self-employment for nonemployment in the next year; these predicted probabilities are roughly twice as high as the 0.082 predicted probability for a representative white worker. Table 4.6 also reveals that each representative worker is substantially more likely to leave self-employment for wage employment than for nonemployment, but that the predicted probabilities of SE-to-WE transitions—which range from 0.27 for whites to 0.35 for Hispanics—do not differ by race/ethnicity nearly as much as the predicted SE-to-NE probabilities.

Table 4.6 reveals that, overall, the representative white has a 0.648 predicted probability of remaining self-employed for the first year, while the corresponding predictions for blacks and Hispanics are 0.516 and 0.497. These black-white and Hispanic-white gaps of 0.13-0.15 percentage points in the predicted probability of

surviving self-employment for one year are substantial, and are sustained over time. I predict that the representative white has 35.1% likelihood of surviving self-employment for five years; this prediction (not shown in Table 4.6), is twice as high as the 17.2% survival probability computed for Hispanics and 0.16 percentage points higher than the corresponding computation of 19.5% for blacks.[28]

In order to determine how much of the racial/ethnic gaps in self-employment exit rates are due to racial/ethnic differences in previous work experience, I recomputed each predicted transition probability after assigning the representative black and Hispanic individual the mean level of each work history variable seen for whites. In other words, I ask how minority workers' predicted exit rates would change if they stayed unchanged in all other respects (schooling attainment, asset levels, *etc.*) but acquire the more "positive" work history of the typical white. Focusing first on transitions to nonemployment, I find that reducing the prior nonemployment rates of Hispanics and blacks to the white mean level of 16% (see Table 4.1) has a substantial effect on the predicted probability of a SE-to-NE transition: the probability falls from 0.155 to 0.146 (8.4%) for Hispanics and from 0.194 to 0.164 (15.4%) for blacks. Surprisingly, when I introduce a similar "improvement" in the prior industry-specific and self-employment experience of Hispanics and blacks, the effects on their predicted SE-to-NE probabilities are small in magnitude and statistically insignificant—and I even find that blacks are slightly more

[28] The predicted one-year survival (SE-to-SE) probabilities in Table 4.6 are lower than the sample transition rates in Table 4.1. Part of the difference between the conditional and unconditional predictions is due to the fact that both SE-to-NE and SE-to-WE transition probabilities decrease with years in the current self-employment job (*i.e.*, reflect negative duration dependence) as shown by the coefficient estimates for duration dummies in Table 4.7. As a result, the *unconditional* probability of one-year survival is higher than the predicted probability of one-year survival *conditioned* on a worker having become self-employed in the current year.

likely to make a SE-to-NE transition when they gain prior self-employment experience. As a result, when I assign minority workers the white means for all three work history variables, virtually the entire estimated effect comes from the change in prior nonemployment experience. While the absolute changes in predicted probabilities due to these interventions may appear to be small, the reductions in predicted SE-to-NE transitions are substantial in terms of the racial gaps. The black-white gap in SE-to-NE transition decreases by 27.2% and the Hispanic-white gap decreases by 18% as a result of minorities being assigned the same (mean) work histories as whites.

While nonemployment experience is the key determinant of SE-to-NE transitions, I find that prior self-employment and industry-specific experiences are important when it comes to exits to wage employment. Table 4.6 shows that lowering prior nonemployment experience to the white mean raises the predicted SE-to-WE probability from 0.290 to 0.312 (7.6%) for blacks. However, an analogous "improvement" in prior industry-specific and self-employment experience lowers the SE-to-WE probability for blacks from 0.290 to 0.276 (4.8%) and from 0.290 to 0.269 (7.2%), respectively. These interventions more than offset the effect of changing nonemployment experience, resulting in a net reduction in the predicted SE-to-WE probability to 0.276 (4.8%) when all three work history variables are equal to the white means; changing all three work history variables lowers the black-white gap in the predicted SE-to-WE probability by a sizable 70.2%. For Hispanics, neither a reduction in nonemployment experience nor a gain in industry-specific experience has economically or statistically significant effects on the predicted SE-to-WE probability. However, an increase in prior self-employment experience is predicted to lower this transition probability from 0.348 to 0.338 (2.9%).

While changing all three work history variables to the white mean lowers the Hispanic-white gap in the predicted SE-to-WE rate by 12.5%, this "overall" effect is imprecisely estimated for Hispanics.

The preceding cause-specific analysis is meaningful because transitions to nonemployment are invariably more damaging to a worker's career than are transitions to wage ("nonself") employment. Nonetheless, in the right-most panel of Table 4.6, I add the effects on SE-to-NE and SE-to-WE probabilities (and subtract from one) to produce "bottom line" estimated effects on one-year survival probabilities. When I change all three work history variables to the white means, the predicted one-year survival rate increases from 0.497 to 0.520 (4.6%) for Hispanics and from 0.516 to 0.560 (8.5%) for blacks. In terms of racial/ethnic gaps, this change is sizable: the black-white gap in the predicted, one-year survival probability narrows by 33.6% and the Hispanic-white gap narrows by 15.2%.

The next few rows of Table 4.6 show how a different intervention—namely, changing three measures of family background and financial status to the white means—affects the predicted probabilities of SE-to-NE, SE-to-WE, and SE-to-SE transitions.[29] My goal is to demonstrate how the estimated effects of work history variables compare to the estimated effects of three variables that have been shown in the literature to be important determinants of self-employment rates: own schooling, father's schooling, and asset levels. For blacks, an increase in years of schooling from the black mean (12.5) to the white mean (13.2) *lowers* the predicted SE-to-NE probability from 0.194 to 0.179 (7.7%) and *raises* the predicted SE-to-WE probability from 0.290 to 0.303 (4.5%). In

[29] In making these computations, I set all other covariates, *including* the three work history variables, equal to the race/ethnicity-specific group means or modes.

other words, increased schooling attainment among blacks is expected to reduce business failures leading to nonemployment, but raise the possibility of receiving an attractive wage offer. These two effects offset each other, resulting in no significant change in the predicted probability of self-employment survival. Interestingly, the remaining two interventions (raising father's schooling from 11.0 to 12.2 years and raising assets from $48,000 to $76,000) are found to have virtually no effect on the predicted SE-to-NE probability, but to lower the predicted probability of SE-to-WE transitions, thereby (slightly) raising the predicted self-employment survival rate. While the effects of assets are imprecisely estimated, assigning blacks the white sample mean value for father's schooling is found to lower their predicted SE-to-WE probability by a statistically significant 7.2% (from 0.290 to 0.269). This produces a 3.7% increase in the predicted probability of survival (from 0.516 to 0.535), which translates into a 14.1% reduction in the black-white gap in the predicted survival rate. While previous research has demonstrated that asset levels and family background are important determinants of self-employment *entry* (Blanchflower and Oswald 1998; Dunn and Holtz-Eakin 2000; Evans and Jovanovic 1989) for minorities as well as whites (Fairlie 1999, 2006; Lofstram and Wang 2006), I find that they are relatively unimportant determinants of self-employment *exits*, especially compared to the effects of individuals' work histories. Moreover, I find that neither father's schooling levels nor asset levels play a role in preventing transitions from self-employment to nonemployment, which is the type of business failure that public policy should be focused on preventing.

These conclusions do not change significantly when I instead focus on the estimated effects seen for Hispanics in Table 4.6. The estimated effects of own schooling

attainment are qualitatively the same for Hispanics and blacks, although the estimates for Hispanics are smaller in magnitude and less precise. An increase in fathers' schooling levels lowers the predicted SE-to-NE probability for Hispanics by a substantial amount (from 0.155 to 0.143), in contrast to the "no effect" seen for blacks, but the estimate for Hispanics has a very large standard error. The estimated effects of assets on SE-to-WE transitions have opposite signs for blacks and Hispanics, but neither effect is estimated with any precision.

Overall, I find that the contribution of own schooling, father's schooling, and assets to the *racial/ethnic* gaps in predicted self-employment survival probabilities is relatively small, which is consistent with the findings in previous studies (Fairlie 1999, Lofstrom and Wang 2006). Specifically, I find that the combined effect of these three variables is due largely to the fact that parental schooling tends to discourage SE-to-WE transitions, and that these factors are not as important as work history variables in explaining racial/ethnic differences in self-employment survival. Raising three background/financial variables to the white means is predicted to close the Hispanic-white gap in self-employment survival by a statistically insignificant 6.2%, and is predicted to close the black-white gap by 21.2%. These predictions are much smaller than the 15.2% and 33.6% attributed to similar changes in three work history variables.

To summarize the predicted effects of additional interventions, I also show in Table 4.6 the predicted transition probabilities corresponding to *all* covariates (including the three work history variables and three schooling/asset variables) being set equal to the sample means or modes among whites. This assumed intervention raises the predicted one-year survival probability from 0.516 to 0.601 (16.5%) for blacks and from 0.497 to

0.532 (7%) for Hispanics. Stated differently, changing all characteristics to the white means/modes reduces the black-white and Hispanic-white gaps in the predicted survival probability by 64.4%and 23.1%, respectively (although the change seen for Hispanics is not statistically significant at a 10% significance level). Changing only three work history variables to the white means raises the predicted self-employment survival probability from 0.516 to 0.560 (8.5%) for blacks, and from 0.497 to 0.520 (4.6%) for Hispanics. Thus, it is apparent that more than half of the "total" increase in predicted self-employment survival rates (from setting *all* covariates equal to white means/modes) is attributable to the role of work history variables.

Because the entire analysis has focused on changing assumed "endowments" for the representative black and Hispanic to values associated with the representative white, I conclude with a different type of experiment: In the last row of Table 4.6, I use white men's coefficient estimates for each covariate to compute predicted transition probabilities of the representative black and Hispanics; I use race/ethnicity-specific means or modes for each covariate for these computations. This experiment allows me to assess the extent to which the predicted racial/ethnic gaps are due to racial/ethnic differences in estimated "returns" (marginal effects) rather than differences in "endowments." For Hispanics, the estimated effect is very large and statistically significant: the predicted SE-to-SE probability increases from 0.497 to 0.603 (21.3%). Put differently, this intervention narrows the Hispanic-white gap in the predicted self-employment survival rate by 69.8%, which is three times as large as the 23.1% reduction due to changing the endowments. This estimated effect on SE-to-SE rates is largely due to the dramatic change in the estimated SE-to-NE probability (0.155 to 0.105), and

reflects the large, statistically significant estimated coefficients for interactions between Hispanic and both "own highest grade completed" and "father's highest grade completed" (Table 4.7). For blacks, the effect of this experiment on the predicted SE-to-SE rate is small and insignificant, while the predicted SE-to-WE probability increases significantly from 0.290 to 0.357. The results from this intervention suggest that racial/ethnic differences in the processes determining self-employment exits are substantial, especially between Hispanics and whites. However, I have chosen to focus on the role of racial/ethnic differences in endowments in contributing to minority-white gaps in self-employment survival because endowments can potentially be manipulated by public policy.

4.7 Conclusion

Cross-sectional data have consistently shown that black and Hispanic workers are far less likely than their white counterparts to be self-employed. Using a sample of male workers observed from ages 22 to 40, I find that racial/ethnic differences in self-employment *exit* rates—*not* entry rates—explain much of the racial/ethnic disparity in cross-sectional self-employment rates. Stated differently, blacks and Hispanics do not lag behind whites in their rates of self-employment entry nearly as dramatically as they lag behind whites in their self-employment survival rates. Further, I find that the relatively high self-employment exit rates seen among minority workers are driven largely by transitions to nonemployment.

Estimates from a cause-specific model of self-employment exits show that work history variables are important determinants of racial/ethnic differences in self-

employment exit rates. Spending a large percent of time nonemployed prior to self-employment is predicted to significantly raise the probability of leaving self-employment for nonemployment. In addition, spending a large percent of time in the same industry or in self-employment prior to current self-employment is predicted to significantly raise the likelihood of business survival by lowering transitions to alternative "wage" jobs. Because minority workers often enter self-employment with relatively weak work histories (*i.e.*, having spent a large percent of time nonemployed and not accumulating industry-specific experience), they have relatively low predicted probabilities of business survival. Specifically, I find that improving a representative black (Hispanic) worker's work history to resemble that of a representative white worker is expected to reduce the black-white (Hispanic-white) gap in self-employment survival by 34% (15%). The combined contribution of the three work history variables that I consider is much larger than the combined contribution of the individual's schooling attainment, his father's schooling attainment, and his asset levels; I find that raising these three variables to the white means can be expected to lower the black-white self-employment survival rate by 21%, and the Hispanic-white rate by only 6%.

In short, I find that weak attachment to the labor market, lack of industry-specific experience, and lack of prior self-employment experience are important factors in explaining why minority self-employment spells tend not to last—and failure to survive in self-employment, rather than failure to enter self-employment in the first place, is where minorities lag behind whites the most. These results suggest that school-to-work programs that raise the early-career employment stability of minority workers and other policies designed to provide minority workers with opportunities to accumulate related

experience are needed to promote successful minority businesses. Based on my findings, I conjecture that such programs may play a bigger role in closing the minority-white self-employment gap than will policies aimed at helping to finance minority-owned businesses.

	Hispanic		Black		White	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Sample transition rates (%)						
SE to SE	73.78		72.59		80.64	
SE to NE	10.84		11.65		5.18	
SE to WE	15.38		15.76		14.18	
Labor market experiences						
Percent of time nonemployed[ac]	21.50	24.47	28.10	27.69	16.22	22.24
Percent of time working in same industry[ac]	33.13	37.23	31.90	37.54	44.50	41.07
Percent of time self-employed[ac]	20.51	32.43	15.16	29.39	26.96	38.23
Age at start of spell[ac]	29.60	5.25	30.84	5.13	28.90	5.27
Family and financial backgrounds						
Highest grade completed at start of spell[c]	11.79	3.01	12.48	2.02	13.20	2.40
Father's highest grade completed[c]	9.41	5.02	10.97	2.71	12.18	3.30
Net assets at start of spell[bc]	-0.06	3.10	0.48	1.37	0.76	3.74
Other controls						
1 if born abroad	0.37		0.02		0.02	
1 if married[c]	0.52		0.33		0.61	
1 if divorced or separated[c]	0.14		0.20		0.14	
Number of children in the household[c]	1.13	1.44	0.71		0.98	
County unemployment rate[c]	7.57	3.49	6.30	2.52	6.47	2.76
1 if live in urban area[c]	0.91		0.89		0.69	
Industry dummy variables[d]						
1 if construction	0.18		0.26		0.28	
1 if manufacturing	0.02		0.03		0.04	
1 if transportation/communication	0.09		0.08		0.05	
1 if trade	0.10		0.06		0.09	
1 if finance/insurance/real estate	0.03		0.03		0.04	
1 if business service	0.10		0.07		0.07	
1 if repair service	0.14		0.16		0.08	
1 if professional service	0.03		0.03		0.05	
1 if health service	0.02		0.00		0.02	
1 if other service	0.15		0.17		0.11	
1 if industry code missing	0.02		0.01		0.04	
Number of observations	1,125		1,390		4,653	

Note: The model also includes dummy variables indicating whether the worker is black or Hispanic (with white the omitted group), and five dummy variables indicating current spell duration; six years or more is the omitted category.

[a] Measured from 22nd birthday to start of the self-employment spell.

[b] Deflated by the CPI-U and expressed in hundreds of thousands of 2002 dollars.

[c] Interacted with both the black and Hispanic race/ethnicity indicators.

[d] Agriculture/fishery is the omitted category.

Table 4.1: Summary statistics for variables used in multinomial logit model

	Hispanic	Black	White	All
1979 National Longitudinal Survey of Youth				
Percent who are ever self-employed (ages 22-40)	30.9	28.7	36.5	33.1
[Sample size]	[777]	[1,214]	[2.045]	[4,036]
Percent who are self-employed in interview week	6.5	5.1	9.5	7.8
[Sample size]	[9,287]	[13,131]	[26,763]	[49,181]
March 2004 Current Population Survey[a]				
Percent who are self-employed in reference week	6.1	5.1	10.0	8.8
[Sample size]	[4,210]	[1,814]	[15,386]	[21,410]

[a] Men ages 22 to 40.

Table 4.2: Alternative self-employment rates, men ages 22 to 40

No. of jobs per person	Hispanic		Black		White		All	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
1	147	61.3	247	71.0	454	60.8	848	63.5
2	60	25.0	68	19.5	178	23.8	306	22.9
3+	33	13.8	33	9.5	115	15.4	181	13.6
All	240	100.0	348	100.0	747	100.0	1,335	100.0
Mean	1.6		1.4		1.6		1.6	
Std. Dev.	1.0		0.8		1.0		1.0	

Table 4.3: Distribution of number of self-employment jobs per person

Duration (month)	Hispanic		Black		White		All	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Less than 12	133	34.6	181	36.3	322	26.2	636	30.1
12 - 35	138	35.9	164	32.9	399	32.4	701	33.2
36 - 59	41	10.7	55	11.0	153	12.4	249	11.8
60+	72	18.8	98	19.7	357	29.0	527	24.9
All	384	100.0	498	100.0	1,231	100.0	2,113	100.0
Mean	38.6		35.8		51.4		45.4	
Std. Dev.	52.3		43.0		61.2		56.2	

Note: If job spell is right-censored, the last interview date is regarded as ending date. For jobs that begin before age 22, the actual start date is used.

Table 4.4: Distribution of durations of self-employment jobs

	Hispanic		Black		White		All	
Percentage	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Panel A: percentage weeks self-employed								
Less than 10	108	45.0	166	47.7	239	32.0	513	38.4
10 – 30	67	27.9	106	30.5	215	28.8	388	29.1
30 – 50	33	13.8	41	11.8	113	15.1	187	14.0
50+	32	13.3	35	10.1	180	24.1	247	18.5
All	240		348		747		1335	
Mean	22.2		18.7		29.8		25.5	
Std. Dev.	23.9		20.3		27.7		25.8	
Panel B: percentage weeks wage employed								
Less than 10	13	5.4	22	6.3	60	8.0	95	7.1
10 – 30	29	12.1	53	15.2	88	11.8	170	12.7
30 – 50	44	18.3	71	20.4	115	15.4	230	17.2
50+	154	64.2	202	58.1	484	64.8	840	62.9
All	240	100.0	348	100.0	747	100.0	1335	100.0
Mean	58.1		54.5		58.2		57.2	
Std. Dev.	26.3		27.0		28.2		27.6	
Panel C: percentage weeks nonemployed								
Less than 10	99	41.3	123	35.3	437	58.5	659	49.4
10 – 30	85	35.4	102	29.3	231	30.9	418	31.3
30 – 50	32	13.3	54	15.5	57	7.6	143	10.7
50+	24	10.0	69	19.8	22	3.0	115	8.6
All	240	100.0	348	100.0	747	100.0	1335	100.0
Mean	19.7		26.8		12.0		17.3	
Std. Dev.	20.1		25.2		14.5		19.8	

Table 4.5: Distribution of percentage weeks self-employed, wage-employed and nonemployed (ages 22 and 40)

	SE to NE			SE to WE			SE to SE (survival rate)		
	Hispanic	Black	White	Hispanic	Black	White	Hispanic	Black	White
Baseline (own means or modes for all covariates)	0.155	0.194	0.082	0.348	0.290	0.270	0.497	0.516	0.648
White means for									
Percent of time spent in nonemployment	0.146*	0.164*		0.351	0.312*		0.503	0.524	
	[12.3]	[26.8]		[-3.6]	[-112.6]		[4.2]	[6.0]	
Percent of time working in same industry	0.152	0.184		0.346	0.276*		0.502	0.541*	
	[3.6]	[9.5]		[2.7]	[70.7]		[3.2]	[18.7]	
Percent of time spent in self-employment	0.153	0.205		0.338*	0.269*		0.509*	0.526	
	[2.2]	[-9.6]		[13.2]	[105.6]		[7.9]	[7.6]	
All three work history variables	0.142*	0.164*		0.339	0.276		0.520*	0.560*	
	[18.0]	[27.2]		[12.5]	[70.2]		[15.2]	[33.6]	
White means for									
Highest grade completed	0.152	0.179*		0.356	0.303*		0.492	0.519	
	[3.6]	[14.0]		[-9.8]	[-63.6]		[-3.3]	[2.3]	
Father's highest grade completed	0.143	0.196		0.333	0.269*		0.524*	0.535*	
	[16.2]	[-1.7]		[19.6]	[104.0]		[18.0]	[14.1]	
Net assets at start of spell	0.153	0.194		0.362	0.285		0.485	0.521	
	[2.2]	[0.4]		[-18.0]	[25.8]		[-8.2]	[4.2]	
All three background/financial variables	0.139	0.180*		0.355	0.276		0.506	0.544*	
	[21.4]	[12.6]		[-8.1]	[69.7]		[6.2]	[21.2]	
White means (or modes) for all covariates	0.124*	0.112*		0.344	0.287		0.532	0.601*	
	[41.7]	[73.2]		[5.6]	[14.6]		[23.1]	[64.4]	
White coefficients for all covariates	0.105*	0.144		0.292	0.357*		0.603*	0.499	
	[67.6]	[44.5]		[72.0]	[-336.9]		[69.8]	[-12.5]	

Note: Each representative individual is 30 years old, is in his first year of self-employment, and has characteristics equal to his race/ethnicity-specific means for continuous variables and modes for dummy variables. The percent reduction in the baseline Hispanic-white or black-white gap associated with the given intervention is shown in brackets.

*Predicted probability is statistically different than the baseline predicted probability at a 10% significance level.

Table 4.6: Predicted probability of transition in the next year

	SE to NE	SE to WE
Hispanic	0.0666 [1.1287]	0.9736 [0.9683]
Black	2.0976 [1.2760]	2.8512 [1.0102]**
Percent of time nonemployed	1.8539 [0.2969]**	-0.3065 [0.2261]
Percent of time nonemployed*Hispanic	-0.4758 [0.5774]	0.3912 [0.5205]
Percent of time nonemployed*black	-0.3005 [0.4740]	-0.1895 [0.4020]
Percent of time working in same industry	-0.3698 [0.2484]	-0.5970 [0.1460]**
Percent of time working in same industry*Hispanic	0.1330 [0.4939]	0.4607 [0.3732]
Percent of time working in same industry*balck	-0.4552 [0.4790]	-0.1697 [0.3300]
Percent of time self-employed	-0.0725 [0.2789]	-0.8246 [0.1800]**
Percent of time self-employed*Hispanic	-0.4602 [0.5473]	-0.0116 [0.4330]
Percent of time self-employed*black	0.3634 [0.5144]	0.0263 [0.4042]
Age	-0.0203 [0.0166]	-0.0569 [0.0106]**
Age*Hispanic	-0.0355 [0.0273]	-0.0453 [0.0231]*
Age*Black	-0.0663 [0.0277]*	-0.0704 [0.0211]**
Highest grade completed	-0.1799 [0.0393]**	-0.0057 [0.0261]
Highest grade completed *Hispanic	0.1748 [0.0590]**	0.0285 [0.0491]
Highest grade completed *Black	0.0558 [0.0637]	0.0556 [0.0484]
Highest grade completed of father	0.0435 [0.0245]+	0.0060 [0.0161]
Highest grade completed of father *Hispanic	-0.0915 [0.0361]*	-0.0413 [0.0270]
Highest grade completed of father *Black	-0.0649 [0.0448]	-0.0961 [0.0343]**
Net assets	-0.0269 [0.0253]	-0.0039 [0.0220]
Net assets*Hispanic	0.0451 [0.0541]	0.0832 [0.0578]
Net assets*Black	-0.0182 [0.1212]	-0.0984 [0.0678]
1 if born abroad	0.0640 [0.2199]	-0.2017 [0.1717]
1 if married	-0.4646 [0.1993]*	-0.4336 [0.1238]**
Married*Hispanic	0.5534 [0.3473]	0.9329 [0.3021]**
Married*Black	0.1043 [0.3408]	0.4903 [0.2718]+
1 if divorced or separated	0.0382 [0.2207]	-0.0750 [0.1582]
Divorced/separated*Hispanic	0.6481 [0.3791]+	0.5677 [0.3610]
Divorced/separated*Black	0.1391 [0.3402]	0.2257 [0.2886]
Number of children in the household	-0.0313 [0.0786]	0.0830 [0.0469]+
Number of children in the household*Hispanic	-0.1614 [0.1289]	-0.2554 [0.0924]**
Number of children in the household*Black	0.1298 [0.1147]	-0.0085 [0.1016]

Continued

Table 4.7. Multinomial logit estimates of exit from self-employment

Table 4.7: Continued

County unemployment rate	0.0288 [0.0252]	0.0361 [0.0167]*
County unemployment rate*Hispanic	0.0207 [0.0378]	-0.0089 [0.0323]
County unemployment rate*Black	0.0417 [0.0453]	-0.0735 [0.0400]+
1 if live in urban area	0.0698 [0.1486]	-0.0160 [0.1025]
Duration = 1st year	2.3262 [0.1799]**	2.1079 [0.1276]**
2nd year	1.3528 [0.1976]**	1.4022 [0.1371]**
3rd year	0.9992 [0.2184]**	0.9434 [0.1556]**
4th year	0.6327 [0.2579]*	0.6725 [0.1798]**
5th year	0.7351 [0.2799]**	0.7192 [0.1876]**
Industry		
1 if construction	0.3068 [0.2029]	0.2556 [0.1445]+
1 if manufacturing	0.6679 [0.3350]*	0.2571 [0.2360]
1 if transportation/communication	0.4970 [0.2444]*	0.0927 [0.1851]
1 if trade	0.5526 [0.2435]*	0.0853 [0.1734]
1 if finance/insurance/real estate	-0.3146 [0.4072]	-0.0641 [0.2445]
1 if business service	0.3253 [0.2481]	0.0019 [0.1914]
1 if repair service	0.2589 [0.2285]	0.2078 [0.1652]
1 if professional service	0.1053 [0.3643]	-0.0813 [0.2496]
1 if health service	0.0159 [0.5758]	-0.6181 [0.4759]
1 if other service	0.4119 [0.2221]+	0.0449 [0.1636]
1 if industry code missing	-0.1633 [0.3857]	-0.0305 [0.2115]
Constant	-2.1080 [0.7711]**	-0.8539 [0.4934]+
Log likelihood	-4041.66	

Note: For industry dummy variables, agricultural/fishery is omitted category. Robust standard errors adjusted for correlation within individual are in brackets.
+ Significant at 10% * Significant at 5% ** Significant at 1%

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