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JEL Classification: D14, G11, G12

Keywords: non-retirement accounts, ownership turnover, Trading Costs, PSID, SCF

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Income Risk and Stock Market Entry/Exit Decisions*

Yosef Bonaparte, George M. Korniotis, and Alok Kumar†

April 9, 2021

Abstract

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1 Introduction

The decision to enter or exit from the stock market is a major portfolio decision. Surprisingly, the extant portfolio choice literature has paid relatively less attention to these entry and exit decisions and has focused more on the market participation decision.[1] For example, Campbell (2006) characterizes the demographics of stockholders and Calvet, Campbell, and Sodini (2007) identify their main investment mistakes. The literature has also considered how stock ownership is affected by health status, social interactions, optimism, trust, financial literacy, and even height and weight.[2] The overall perception in the current literature is that once investors enter the market, they rarely liquidate all of their holdings and leave.

In this paper, we extend the portfolio choice literature and conjecture that income shocks affect ownership turnover in non-retirement accounts.[3] Specifically, in contrast to the existing belief in the literature, we posit that some U.S. households are likely to exit the market due to negative income shocks while other investors are likely to enter or re-enter the market due to positive income shocks. This conjecture is partially motivated by the predictions of canonical portfolio choice models, which posit that investors facing income shocks and liquidity constraints trade the most and exhibit the highest ownership turnover (e.g., Guiso, Jappelli, and Terlizzese (1996)). We are also motivated by related studies, which demonstrate that income shocks are important for asset allocation and stock selection decisions.[4]

Consistent with our conjecture, we find evidence of large turnover in and out of non-retirement accounts among U.S. households. This analysis is based on the biennial waves of

[1] See Vissing-Jørgensen (2002b), Calvet, Gonzalez-Eiras, and Sodini (2004), Calvet, Campbell, and Sodini (2009), Bilias, Georgarakos, and Haliassos (2010), and Fagereng, Gottlieb, and Guiso (2017).

[2] See Rosen and Wu (2004), Hong, Kubik, and Stein (2004), Puri and Robinson (2007), Brown, Ivković, Smith, and Weisbenner (2008), Guiso, Sapienza, and Zingales (2008), Cole, Paulson, and Shastry (2014), and Addoum, Korniotis, and Kumar (2016).

[3] We exclude retirement accounts from our analysis because our focus is on stock market entry and exit decisions and there is almost no trading or turnover in retirement accounts. For example, the data from the Survey of Consumer Finances (SCF) indicate that only 1.05% to 1.39% of households liquidate funds from retirement accounts before retirement. See Section 2.1 for additional details.

[4] See Angerer and Lam (2009), Betermier, Jansson, Parlour, and Walden (2012), Bonaparte, Korniotis, and Kumar (2014), and Betermier, Calvet, and Sodini (2017).

the Panel Study for Income Dynamics (PSID) from 1999 to 2011. We classify households as stockholders if they own stocks directly or indirectly in non-retirement accounts. Since our goal is to examine active stock ownership, we exclude investors who only own stocks in retirement accounts because, as Brunnermeier and Nagel (2008) note, there is little trading in these accounts.[5] Hong, Kubik, and Stein (2005), Bogan (2008), Bonaparte, Cooper, and Zhu (2012) also define stockholders as those who own equity in non-retirement accounts.

Using the PSID data, we find that as a portion of all households (i.e., owners and non-owners) about 7.3% (8.7%) enter (exit) non-retirement accounts during the next two years. As a portion of stockholders, these turnover rates translate to about 28.8% (23.8%) of households exiting (entering) non-retirement accounts by the next survey wave. Further, only 32.8% of owners of non-retirement accounts in 1999 reported owning stocks in these accounts in all subsequent waves until 2011.

We obtain similar results using the Survey of Consumer Finances (SCF) data. In the 2007-09 SCF panel, among households that had non-retirement accounts in 2007, 13.8% sold all their assets in these accounts by 2009. Further, among households that did not have any wealth in non-retirement accounts in 2007, 20% of them opened such accounts in 2009.

Using the PSID and SCF data, we directly test our key conjecture that income risk affects ownership turnover. For the PSID analysis, we estimate cross-sectional regressions where the dependent variables are related to the total number of entries and exits from non-retirement accounts. The main independent variable is the standard deviation of income growth, a proxy for income risk (Guiso, Jappelli, and Terlizzese 1996; Heaton and Lucas 2000). We consider several control variables that include age, gender, race, education, income, and wealth. We find that the coefficient estimates on income risk are positive in all regression specifications. This evidence indicates that income risk affects market entry and exit decisions.

Our results are further strengthened when we use the 2007-09 SCF panel, where we track household-level changes in ownership status and changes in income. We view changes in

[5]Among others see Samuelson and Zeckhauser (1988), Agnew, Balduzzi, and Sunden (2003), Ameriks and Zeldes (2000), and Huberman and Sengmueller (2004).

income as a proxy for income shocks that directly affect the current financial well-being of households. As such, income changes might prompt shifts in investment behavior, especially if financial assets are used to smooth income shocks.

Consistent with this expectation, we find that, among stockholders, an increase in income is related to a lower probability of selling all assets in non-retirement accounts. Conversely, we find that, among non-stockholders, an increase in income is related to an increase in the probability of investing in non-retirement accounts. In all our regression specifications, we control for changes in financial, housing, and retirement wealth to ensure that the changes in income do not reflect changes in these other forms of wealth.

To better interpret these empirical findings, we develop a portfolio choice model that allows for dynamic ownership of stocks. The goal is to examine the extent to which a portfolio choice model that only relies on income shocks can fit stylized facts about equity ownership turnover in non-retirement accounts. To isolate the effects of income shocks on ownership turnover, we do not include behavioral features like overconfidence (Barber and Odean 2001) or cognitive dissonance (Chang, Solomon, and Westerfield 2016) in our model.

Households in the model receive an exogenous stochastic income payment. They decide how much to consume and how much to save in a risky and a risk-free asset. The risky asset reflects investments in non-retirement accounts. Households are subject to short-sale and borrowing constraints (e.g., Alan (2006) and Gomes and Michaelides (2005)).

Households also face costs when owning equity and incur transaction costs when trading. We consider three types of costs.[6] The first type is a fixed cost of participating in the stock market and owning equity. This fixed cost captures expenses such as investment account maintenance fees, which are charged even when the investor is not trading.

The second cost component is trading costs like brokerage fees, commissions, and the bid-ask spread. The trading costs are proportional to the value of the trade. We acknowledge

[6]See Luttmer (1999), Campbell, Cocco, Gomes, and Maenhout (2001), Paiella (2001), Vissing-Jørgensen (2002b), Calvet, Gonzalez-Eiras, and Sodini (2004), Paiella (2004), Alan (2006), Paiella (2007), Attanasio and Paiella (2011), and Bonaparte, Cooper, and Zhu (2012).

that trading costs have been decreasing over time (Bogan 2008). However, investors are still exposed to the bid-ask spread, and it is important to include this cost in the model.

The third cost component is a per-period portfolio management cost. If investors choose to directly self-manage their portfolio, they incur a reduction in income related to the time spent managing their portfolios. Alternatively, if they delegate their portfolio management task to an advisor, they pay a management fee based on the value of the portfolio.

To keep the model manageable, we ignore life-cycle considerations, especially because our data shows that life-cycle considerations do not seem to affect ownership turnover in non-retirement investment accounts. Specifically, we perform our empirical analysis with the PSID and SCF data *excluding* the very young and the very old for whom life-cycle effects are the strongest (Fagereng, Gottlieb, and Guiso 2017). By focusing on households aged 35 to 60, we find results that are almost identical to our full sample results, which suggests that life-cycle factors are not very important in our context.

We estimate our model with the simulated method of moments (SMM). The estimation matches household-level moments related to ownership decisions, portfolio adjustment frequency, and wealth ratios. We also consider moments related to the reaction of aggregate consumption growth to stock market returns. The aggregate moments ensure that the aggregate implications of the model are consistent with market-level stylized facts. The model is estimated at the quarterly frequency and we aggregate up the simulated data to match the frequencies of the data moments, which vary from quarterly to annual and bi-annual.

We estimate model parameters that include the discount factor, the coefficient of relative risk aversion, and the cost associated with portfolio self-management. To reduce the complexity of the SMM estimation, we do not estimate the proportional trading costs function or the household income process. Instead, we estimate the proportional cost function directly using the brokerage investor data set of Barber and Odean (2000). We also estimate the household-level income process directly using data from the PSID.

The estimation results reveal that the model can effectively capture the decision to own stocks as it is not rejected by the J-test of over-identifying restrictions. In particular, the model captures the persistence in stock ownership and the average ownership rate. It also captures the average entry/exit rates in non-retirement accounts relatively well. However, it predicts higher equity shares compared to the data. The good fit of the model does not come at the expense of unreasonable preference parameter estimates. For example, the estimated coefficient of relative risk aversion and discount factor are 3.087 and 0.970, respectively. These estimates are close to those obtained in the literature (Cagetti 2003; Bonaparte, Cooper, and Zhu 2012).

We use the estimated model to examine how the equity ownership turnover is affected by the cost of equity ownership and trading. We find that fixed-type ownership costs and proportional trading costs have very little explanatory power for entry/exit decisions. For ownership turnover, the most relevant cost is the per-period rebalancing cost, which represents the time cost of trading. We estimate this cost to be 1.20% of current income.

To identify the sources of risk that are most important for the dynamic decision to own stocks, we modify our baseline model. Specifically, we use the baseline estimates and simulate a model where households face an exogenous increase in their idiosyncratic income risk. We also consider an increase in equity risk via the introduction of a stock market crash, similar to Fagereng, Gottlieb, and Guiso (2017).

We find that the model with amplified idiosyncratic income shocks leads to a higher ownership turnover rate than the baseline model. In contrast, the ownership turnover in the model with amplified equity risk is almost identical to that of the baseline model. We also find that the model with the stock-market crash effectively fits various wealth moments such as equity share. These results confirm our main conjecture that income shocks are especially important for ownership dynamics and market entry/exit decisions.

Our findings make important contributions to the literature on retail investors. The current literature on retail investor behavior focuses on trading and puts relatively less emphasis on the entry/exit aspects of stock ownership (Odean 1999; Barber and Odean

2000). To explain trading behavior, Grossman and Stiglitz (1980) suggest that investors equate the marginal benefit of trading to its marginal cost. Motivated by this principle, a large literature examines the impact of transaction costs on portfolio decisions.[7] In addition, Barber and Oden (2000, 2001) suggest that overconfidence drives excessive trading.

Other studies find that households adjust their portfolios in response to changes in wealth, income, and age, as well as stock market performance and volatility.[8] For example, Brunnermeier and Nagel (2008) find that changes in liquid wealth are related to the decision to enter and exit the market. Calvet, Campbell, and Sodini (2009) find that the probability of entry (exit) is higher (lower) for households with higher wealth, income, and education. Bilias, Georgarakos, and Haliassos (2010) show that young, White, healthy, college graduates with high income and high wealth trade the most.

Grinblatt and Keloharju (2000, 2001) find that the trading of retail investors is affected by past returns. Barrot, Kaniel, and Sraer (2016) find that in 2008, French retail investors were selling stock funds and buying individual stocks. Dorn and Weber (2017) show that households that delegate their investments have a higher probability of exiting the market during a crisis relative to households that directly own stocks.

The literature has also identified various other factors that affect portfolio decisions. They include health status (Rosen and Wu 2004), social interactions (Hong, Kubik, and Stein 2004; Brown, Ivković, Smith, and Weisbenner 2008), optimism (Puri and Robinson 2007), trust (Guiso, Sapienza, and Zingales 2008), and financial literacy (Cole, Paulson, and Shastry 2014). Other work finds that risk-taking behavior is affected by height and weight (Addoum, Korniotis, and Kumar 2016) as well as personal experiences (Malmendier and Nagel 2011). We complement these studies and highlight the importance of income risk for the dynamic decision to own stocks.

[7] Among others, see Constantinides (1976), Constantinides (1986), Dumas and Luciano (1991), Gennotte and Jung (1994), Longstaff (2001), Liu and Loewenstein (2002), and Gârleanu and Pedersen (2013).

[8] See Haliassos and Bertaut (1995), Heaton and Lucas (1996), Bertaut and Haliassos (1997), Gollier (2001), Viceira (2001), Campbell and Viceira (2002), Haliassos and Michaelides (2003), Cocco, Gomes, and Maenhout (2005), and Gomes and Michaelides (2008).

In a related paper, Alan (2006) studies the decision to own stocks in a model with fixed market participation costs. She estimates her model with SMM by matching moments from the 1984 and 1989 waves of the PSID. Further, Bonaparte, Cooper, and Zhu (2012) ignore the decision to participate in the market and instead focus on how consumption smoothing and portfolio rebalancing are affected by portfolio adjustment costs. We extend this literature and examine the dynamic decision to enter/exit the market using a more comprehensive portfolio choice model, which is estimated with a more extensive set of moments.

In another related study, Calvet, Gonzalez-Eiras, and Sodini (2004) build a model with income risk to study the impact of financial innovation on stock ownership turnover. Recently, Fagereng, Gottlieb, and Guiso (2017) use data from Norway and find that younger households with lower wealth enter and exit frequently while retired households slowly exit the stock market. They also build a model where investors have constant relative risk aversion preferences, incur a per-period cost to own stocks, cannot borrow, and cannot short-sell stocks. Their model also incorporates a stock-market crash. Complementing their work, we find that extreme equity shocks (like a crash) are less important than idiosyncratic income shocks for fitting the equity ownership turnover.

More broadly, our findings shed further light on the identity of the marginal investor since individuals who bear financial risk change considerably over time. Existing asset pricing studies that use factors related to the consumption of stockholders define marginal investors as those who own stocks in a particular period, ignoring their ownership history (Mankiw and Zeldes 1991; Vissing-Jørgensen 2002a; Brav, Constantinides, and Geczy 2002). However, Malloy, Moskowitz, and Vissing-Jørgensen (2009) highlight the importance of long-run consumption risk of stockholders in fitting the cross-section of expected returns. If long-run risk is important, then our results suggest that we should focus on the consumption growth risk of stockholders with a long history of stock ownership.

The rest of the paper is organized as follows. Section 2 reports key statistical evidence related to ownership turnover. Section 3 examines the empirical relation between income risk and equity ownership turnover. Section 4 presents our portfolio choice model and Section 5 reports the model estimates. Section 6 concludes with a brief discussion.

2 Ownership Turnover: Stylized Facts

We begin our empirical analysis by quantifying the ownership turnover in non-retirement accounts using data from the Panel Study of Income Dynamics (PSID) and the Survey of Consumer Finances (SCF). We report the definitions of all our variables in Appendix A.1.

2.1 Identifying Stockholders

To examine active stock ownership, we identify as stockholders individuals who own stocks in non-retirement accounts only, i.e., investors who directly or indirectly own shares of publicly held corporations, mutual funds, or investment trusts. We exclude ownership in retirement accounts because, as Brunnermeier and Nagel (2008) note, there is minimal trading in these accounts.[9] Other studies have also excluded non-retirement accounts from their analysis, including Hong, Kubik, and Stein (2004), Bogan (2008), and Bonaparte, Cooper, and Zhu (2012).

To confirm the low trading in retirement accounts, we use the Survey of Consumer Finances (SCF) data to investigate whether households with retirement accounts withdraw funds from them before retirement. This information is available in the triennial waves of the SCF after 2004. Focusing on households below 60 years of age, we find that, in 2004, about 1.05% of individuals withdraw some funds from retirement accounts. This statistic is very similar in subsequent SCF waves, including the latest one in 2019. This finding is not surprising since withdrawing from retirement accounts is penalized with very high tax rates.

[9] Also, see Samuelson and Zeckhauser (1988), Agnew, Balduzzi, and Sunden (2003), Ameriks and Zeldes (2000), and Huberman and Sengmueller (2004).

2.2 Ownership Turnover: Evidence from the PSID

The Panel Study for Income Dynamics (PSID) reports biennial panel data on household income and wealth. We focus on the 1999 to 2011 waves. We treat the 1999 wave as the benchmark year and track households for which we know their participation status in all waves until 2011. The sample starts in 1999 because the pre-1999 data do not allow us to separate investments in retirement and non-retirement accounts. Also, prior to 1999, information on combined stock ownership in retirement and non-retirement accounts is only available in the 1984, 1989, and 1994 waves. The sample ends in 2011 to facilitate comparisons between the PSID results and our other main data set, the 2007-09 Survey of Consumer Finances panel. With this choice, our main data sets end at approximately the same time.

We report various stock ownership statistics in Table 1. In Column (1), we report the ownership rates per wave. We see that in 1999 about 30% of the households owned non-retirement accounts. By 2011, the ownership rate drops to 22.6%. This pattern suggests that some of the original 1999 stockholders have permanently liquidated their non-retirement accounts. To better understand this phenomenon, we also report entry and exit statistics.

Specifically, in Column (2) of Panel A, we report the fraction of new stockholders in year $t+2$, i.e., the number of households that did not own stocks in year t but became stockholders in year $t+2$, as a proportion of all households in year t. This statistic reveals that 9.7% of households that were not stockholders in 1999 become stockholders in 2001.

In Column (3) of Panel A, we present the exit statistics. We report the fraction of stock owners in year t that liquidate their positions in year $t+2$. In the 2001 wave, this fraction was 7.5%. On average, 7.3% (8.7%) new households enter (exit) non-retirement accounts between the two waves, which signifies a substantial ownership turnover.

Given that many households do not participate in the stock market, the turnover rates in columns (2) and (3) understate the level of the ownership turnover. Therefore, we express the turnover rates as a portion of households that own stocks. In Column (4), we report the number of non-stockholders in year t who invest in non-retirement accounts in year $t+2$ as a fraction of stockholders in year t. In Column (5), we report the number of stockholders in year t who exit non-retirement accounts in year $t+2$ as a fraction of stockholders in year t.

These statistics indicate that changes in participation status are quite large. For example, about 30.9% of non-stockholders in 1999 open a non-retirement account in 2001. Also, about 23.9% of stockholders in 1999 liquidated their non-retirement account by 2001. On average, the entry rate is about 23.8% and the exit rate is about 28.8%.

2.3 Long-term Stock Ownership

To examine the long-term ownership in non-retirement accounts, we focus on households that owned non-retirement accounts in the 1999 wave. Then, we track their entry and exit decisions from 2001 to 2011. We report their entry/exit frequencies from these subsequent waves in Panel B of Table 1.

We find that many of the 1999 stockholders exit non-retirement accounts permanently. For example, as reported in Column (1), about 76.1% of 1999 stockholders own non-retirement accounts in the 2001 wave, which implies that about 23.9% of them exit from these accounts (see Column (2)). Subsequently, about 5% of them liquidate their non-retirement accounts every two years. By 2011, only 50.8% of 1999 stockholders own non-retirement accounts (see last row of Column (1)). Also, only 32.8% of them participate in these accounts in all waves (see Column (3)). Finally, as reported in Column (4), the fraction of households that exits non-retirement accounts and then re-enters diminishes across waves.

These statistics are robust and they are similar when we track the behavior of those who owned non-retirement accounts in 2001 or 2003. In Panel A of Figure 1, we show that about 32.5% (26.7%) of the 2001 (2003) stockholders do not own any non-retirement accounts after two years. Further, during the 2003 to 2011 period, about 4.3% of the 2001 stockholders exit non-retirement accounts every two years. Similarly, during the 2005 to 2011 period, about 6.3% of the 2003 stockholders exit non-retirement accounts every two years.

One potential concern with these turnover statistics we report is that they might be related to using stock market accounts as "play money" for entertainment purposes or sensation-seeking by investors prone to behavioral biases (Dorn and Sengmueller 2009; Grinblatt and Keloharju 2009; Korniotis and Kumar 2013). To rule out this possibility, we track the participation history of two groups of stockholders: those with stock holdings of less than $300 in 1999, an amount that can be considered as "play money", and those with at least $300 or more. We compute the portion of households in these two groups that owned stocks in any subsequent wave after 1999 and plot them in Panel B of Figure 1.

The results in Figure 1 suggest that the ownership history of an investor is not significantly affected by the initial amount of stock holdings. On average a significant portion of both groups of stockholders exit by 2011: about 30% for those with less than $300 and about 23% for those with more than $300. Subsequently, more of the 1999 investors exit but those with less than $300 exit a bit more.

Overall, investors with low initial stock holding trade slightly more, but these stockholders are a very small portion of the sample. For example, in year 1999, they represent only 1.4% of the sample. Consequently, these households are likely to have little effect on the average entry/exit rates that we report in Table 1.

2.4 Ownership Turnover: Evidence from the SCF

For robustness, we report entry and exit statistics using data from the Survey of Consumer Finances (SCF). The main SCF is a triennial repeated cross-sectional survey that includes different households in each wave. From the triennial surveys, we use the waves during the 1989 to 2011 period and extract mainly wealth-related statistics.

We also use the 2007-09 SCF panel. This is a unique panel because in 2009, due to the financial crisis, the Federal Reserve sponsored a re-interview of the 2007 surveyed households. According to the Federal Reserve, the re-interview was motivated by an effort to understand the effects of the financial crisis on U.S. households. We use this panel to track changes in ownership of non-retirement accounts across the 2007 to 2009 period.

In Table 2, Panel A, we report participation rates in non-retirement accounts in 2009, conditional on the participation status in 2007. We find that 37.1% of households do not participate in non-retirement accounts in either of the two years, while 46.2% of households have some wealth in non-retirement accounts in both years. Further, about 9.3% of households enter and invest in non-retirement accounts in 2009 but not in 2007. Also, 7.4% of households own in non-retirement accounts in 2007 but decide to exit by 2009. These non-retirement account statistics imply that only 73.4% of stockholders in 2007 are also stockholders in 2009.[10] Overall, the statistics from the SCF sample support our conclusion from the PSID that there is substantial turnover in ownership in non-retirement accounts.

Beyond the broad ownership statistics, the SCF sample contains detailed information about the portion of wealth allocated to risky assets. We report those wealth statistics in Panel C of Table 2.[11] We use these wealth data to infer the economic magnitude of the dollar amount bought and sold in non-retirement accounts. Specifically, in Panel D of Table 2, we compare the volume of shares bought and sold to the average equity held in non-retirement accounts and to the average labor earnings of stockholders in 2009.

We find that the average value of equity sold (bought) by exiting (entering) households in non-retirement accounts is 32.8% (14.1%) of the average equity held by all stockholders in 2009. The value of exits and entries is 66.6% and 28.7% of 2009 average labor earnings, respectively. These estimates indicate that turnover in non-retirement accounts is a large share of the average equity held and an even larger share of the average stockholder wages.

[10] We obtain the 73.4% number as follows: from Panel A of Table 2, we know that only 46.2% of households owned non-retirement accounts in 2007 and 2009, 9.3% of households owned such accounts in 2009 but not 2007, and 7.4% of households were owners in 2007 but not in 2009. Therefore, all the households that owned non-retirement accounts in either the 2007 or 2009 waves are: 7.4% + 9.3% + 46.2% = 62.9%. Because only 46.2% were owners in both waves, then 73.4% (= 46.2 / 62.9) of the owners in 2007 are also owners in 2009.

[11] Even after 1999, the PSID does not provide wealth information to separate the portion of wealth allocated to retirement and non-retirement investment accounts.

2.5 Life-cycle Factors and Ownership Turnover

The household finance literature considers life-cycle aspects important for both modeling and measurement of household decisions (Cocco, Gomes, and Maenhout 2005; Campbell 2006). For example, Fagereng, Gottlieb, and Guiso (2017) find that entry and exit decisions are very different between young and old households.

Given this evidence, one concern could be that our results are biased by the behavior of younger and/or older households. To ensure that this is not the case, we re-examine the ownership turnover statistics from both the PSID and SCF using a sub-sample of households in the 35 to 60 age-group. We exclude both the very young and the very old households as these cohorts face the strongest life-cycle influences in their investment decisions (Fagereng, Gottlieb, and Guiso 2017). We present the results with the age-restricted samples in Tables A.2.1 through A.2.3 in the Appendix.

We find that the subsample ownership turnover statistics are almost identical to those obtained with the full sample of households. For example, in the full (age-restricted) PSID sample, the entry and exit rates as a proportion of all households are on average 7.3% and 8.7% (7.1% and 8.8%), respectively. See Columns (1) and (2) in Panel A of Tables 1 and A.2.1. Most importantly, the data moments we use to fit our model in Section 5 are almost identical between the age-restricted and unrestricted samples. Specifically, in the full (age-restricted) sample, the average entry/exit rate in non-retirement accounts is 16% (15.8%), the average proportion of households that always participates in non-retirement accounts is 32.8% (30.4%), and the median value of financial wealth to wages among non-retirement account owners is 1.034 (1.118).

Overall, the similarities in statistics across the two samples suggest that investment decisions in non-retirement accounts are unlikely to be strongly influenced by life-cycle factors. To avoid introducing any potential data-mining and sample selection biases, we use the full sample of households in our empirical analysis.

2.6 Comparison to Existing Results

One potential concern with our turnover rate estimates may be that they suffer from sample-specific biases. We find that this is not the case since our estimates are comparable with the findings of existing studies. For example, Bilias, Georgarakos, and Haliassos (2010) also use the PSID. They report that over the 1999 to 2003 period, the entry and exit rates are 11.4% and 9.9%, respectively (see their Table 4). As we report in Panel A of Table 1, the average entry (exit) rates over the 1999 to 2003 period in our sample is 8.4% (8.9%).[12]

The turnover rates are slightly different in studies that use European data. Calvet, Campbell, and Sodini (2009) report that among Swedish households, the entry rate (15.8%) is substantially higher than the exit rate (1.9%) over the 1990 to 2000 period (see their Table 5), most probably due to the booming stock market around that time. In 2001 (2002), the entry rate decreases to 5.7% (4.4%) and the exit rate rises to 3.4% (3.9%). Using a large and long sample from Norway, Fagereng, Gottlieb, and Guiso (2017) find entry and exit rates that are higher than Calvet, Campbell, and Sodini (2009) and closer to what we report in Tables 1 and 2. In particular, their Figure 2 suggests that, over the 1995 to 2009 period, the average entry rate is about 8.1% while the average exit rate is about 6.9%.[13]

3 Income Risk and Ownership Turnover

Having established that there is significant turnover in stock ownership, in this section, we investigate the degree to which income risk affects the entry and exit decisions of households in non-retirement investment accounts. Specifically, we report results from using the PSID and the 2007-09 SCF panel.

[12] There are some differences between our sample and the sample in Bilias, Georgarakos, and Haliassos (2010) because we focus on households that have valid information about their ownership status in every wave from 1999 to 2011. In contrast, the sample in Bilias, Georgarakos, and Haliassos (2010) ends in 2003.

[13] We do not have access to the data in Fagereng, Gottlieb, and Guiso (2017), so we compute these averages with back-of-the-envelope calculations using their Figure 2, which reports entry/exit rates for different age cohorts.

3.1 PSID Regression Estimates

Our regression tests with the PSID are based on the core intuition of portfolio choice models about stock ownership. As Guiso, Jappelli, and Terlizzese (1996) point out, theoretically, trading should be driven by the desire to smooth income shocks. Thus, investors facing high income risk and liquidity constraints would be forced to enter/exit the market often.

We examine this theoretical prediction by estimating cross-sectional regressions. The dependent variables measure ownership turnover in non-retirement accounts. The main independent variables are income and wealth, which serve as proxies for liquidity constraints (Runkle 1991; Guiso, Jappelli, and Terlizzese 1996). The other important independent variable is the standard deviation of income growth, which is our proxy for income risk (Guiso, Jappelli, and Terlizzese 1996; Heaton and Lucas 2000). The control variables in the regressions are various demographic characteristics such as age, race, gender, and education.[14]

For the estimation, we use data from the 1999 to 2011 biennial waves of the PSID. We exclude households that never had a non-retirement account during the 1999 to 2011 period to focus on those households that might have used risky assets as a vehicle to smooth income shocks. By excluding households that never invested in non-retirement vehicles, we can also separate the participation decision from the active decision to trade stocks. Finally, we exclude households with income growth higher than 300% and lower than −70% to mitigate concerns related to measurement and reporting errors.

We present summary statistics for the regression variables in Panel A of Table 3. In Panel B of Table 3, we present the estimation results. We report results for measures related to the turnover in and out of non-retirement investment accounts over the 1999 to 2011 period. In particular, the dependent variables in Regressions (1), (2), and (3) are the log of 1 plus the total number of entries, exits, and entries and/or exists from non-retirement accounts, respectively. In Regressions (4), (5), and (6), the dependent variable is a dummy variable that takes the value of 1 if the household has at least one entry, one exit, and one entry or

[14] Detailed definitions of all variables are provided in Appendix A.1.

exit during the sample period, respectively. We estimate Regressions (1) to (3) with ordinary least squares and estimate Regressions (4) to (6) with a probit estimator.

Consistent with our conjecture, we find that income risk and liquidity constraints are related to the decision to enter and exit the market. Specifically, the coefficient estimates of the standard deviation of income growth are positive in all regressions and statistically significant in all instances except Regression (5). Further, the coefficient estimates for our liquidity constraint proxy (i.e., wealth) are always negative and statistically significant. The estimates for income are negative and less significant. The estimates also confirm previous findings that demographic characteristics like age, education, and gender affect the entry/exit decisions (Calvet, Campbell, and Sodini 2009; Bilias, Georgarakos, and Haliassos 2010).

3.2 2007-09 SCF Panel Regression Estimates

We use the 2007-09 SCF panel to further analyze how income shocks affect the ownership of non-retirement investment vehicles. With the SCF panel, we track the changes in the ownership status of a particular household. This allows us to provide a more direct test of whether changes in ownership status are related to changes in their income.

We conjecture that income changes proxy for income shocks and they should directly affect investment behavior, especially if financial assets are used to smooth income shocks. Therefore, our prediction is that an increase in income should decrease the probability of selling all assets in non-retirement accounts. Conversely, an increase in income should increase the probability of investing in non-retirement accounts.

For the estimation, we create two sub-samples. The first sub-sample includes the stockholders (i.e., owners of non-retirement accounts) in 2007. Using this sample, we examine the factors that can increase the probability of the 2007 stockholders to exit in 2009. The second sub-sample includes the non-stockholders (i.e., households with no wealth in non-retirement accounts) in 2007. With this sub-sample, we examine the factors that can increase their probability to invest in non-retirement accounts in 2009. In our regression analysis, we also control for changes in financial, housing, and retirement wealth to ensure that the changes in income are not reflecting changes in these other forms of wealth.

We estimate various probit regressions and report the marginal effects in Table 5. In Columns (1) and (2), the dependent variable takes the value of 1 if an owner of non-retirement accounts in 2007 exited in 2009. In Columns (3) and (4), the dependent variable takes the value of 1 if a household did not invest in non-retirement accounts in 2007 but reports owning non-retirement accounts in 2009. The main independent variable is the change in labor income from 2007 to 2009. We also follow Guiso, Sapienza, and Zingales (2018) and control for key demographic variables (e.g., race, gender, age, education, income, wealth, and risk tolerance) as of the year 2007. We measure the demographics as of 2007 because we build the sub-samples based on the ownership status of the household as of 2007. We also control for changes in retirement, financial, and housing wealth. For comparison, we do not include the changes in income and wealth measures in Regressions (1) and (3), and we add them in Regressions (2) and (4).

Consistent with our conjecture, we find that changes in income affect financial decisions. The estimates suggest that an increase in income is associated with a lower probability of exiting and a higher probability of entering the market. The marginal effect of income changes is statistically significant even in the presence of all our control variables that include changes in retirement, financial, and housing wealth.

We also find that changes in income and various forms of wealth have higher marginal effects in the entry regressions. This finding is consistent with Calvet, Campbell, and Sodini (2009) who also find that income, financial wealth, and real estate wealth affect the entry decision more than the exit decision. Other coefficient estimates are also meaningful. We find that more educated individuals have a lower (higher) probability of exiting (entering) non-retirement accounts. More wealthy households with higher income behave similarly.

One concern with our results is that the 2007 to 2009 period is around an economic recession. As such, entries in the market might be driven by investors acting as contrarians (e.g., Grinblatt and Keloharju (2000, 2001)). However, such contrarian behavior should be reflected in changes in financial wealth that we control for in our regressions. Also, the literature on wealth effects (Poterba 2000; Lettau and Ludvigson 2004; Paiella and Pistaferri 2017) suggests that investors might exit the market as a response to decreases in their overall wealth. For this reason, we control for changes in financial, housing, and retirement wealth. We find that conditional on these wealth changes, average wealth and income levels, and risk tolerance, changes in income influence ownership turnover.

Collectively, the empirical evidence from the SCF and the PSID confirms our conjecture that income risk affects stock ownership decisions. Households with high income risk have higher turnover in and out of non-retirement accounts. In addition, changes in income levels affect the probability of entry and exit from non-retirement accounts.

4 A Model of Portfolio Choice with Income Risk

In this section, we develop a theoretical framework to examine household stock ownership decisions. The model allows us to assess the impact of important determinants of equity ownership, such as the opportunity cost of managing a portfolio as well as liquidity constraints. These factors are typically not observed or are difficult to measure. We use our model to quantify their relative importance.

4.1 Dynamic Optimization Problem

In the model, individuals can invest in a risky or a riskless asset. Their trading activities are limited by short-sale and borrowing constraints as well as equity ownership and transaction costs. They also face uninsurable income shocks that can be smoothed by investing.

Individuals in the model are ex-ante identical. We acknowledge that investor heterogeneity driven by demographic characteristics influences portfolio decisions due to life-cycle considerations (Cocco, Gomes, and Maenhout 2005; Gomes and Michaelides 2005; Fagereng, Gottlieb, and Guiso 2017). We abstract from such considerations and consider a relatively simple portfolio choice model. Our choice is motivated by the observation that the household moments we use in the estimation of the model are not materially affected when we exclude the very young and the very old investors for whom life-cycle considerations are the strongest. See Table A.2.3 in the Appendix for the age-restricted and full-sample moments.

In the model, investors make decisions using the value function v. The value function is the investor's maximum over the options of adjusting or not adjusting his holdings. That is:

$$v(y, s_{-1}, b_{-1}, R_{-1}) = max\{v^{\alpha}(y, s_{-1}, b_{-1}, R_{-1}), v^{n}(y, s_{-1}, b_{-1}, R_{-1})\}, \tag{1}$$

where v^{α} and v^{n} are the value functions associated with the decision to adjust and not adjust asset holdings, respectively.

The arguments of the value function are y, s_{-1}, b_{-1}, and R_{-1}. y is the investor's stochastic income. Income follows a persistent five-state Markov chain that we estimate using data from the PSID. We provide more details about the income process in Section 4.2.3 and Appendix A.3. s_{-1} is his holdings of the risky asset at the beginning of the period. The return from these holdings is R_{-1}. The holdings of the riskless asset are b_{-1} with return r. The total financial wealth at the start of a period is $R_{-1}s_{-1} + rb_{-1}$.

With s, we denote the value of risky assets at the end of the period. We assume that investors cannot short and set the lower bound of s at $\bar{s} = 0$. We eliminate shorting because most retail investors cannot easily short stocks. With b, we denote the value of bond holdings at the end of the period, which is bounded below by $\bar{b}$. While we can allow for borrowing in the model, we find that the best model fit arises with tight borrowing constraints in which the investor cannot borrow (that is, $b \geq 0$). Our choice to prohibit borrowing is consistent with the literature (for example, see Aiyagari (1994), Heaton and Lucas (1996), Alan (2006), Gomes and Michaelides (2008) and Fagereng, Gottlieb, and Guiso (2017)).

4.1.1 Value Function Under Portfolio Adjustment

If the stockholder chooses to adjust his portfolio, then his value function v^{α} is given by:

$$v^{\alpha}(y, s_{-1}, b_{-1}, R_{-1}) = max_{\ s \geq \bar{s},\ b \geq \bar{b}}\ \ u(con) + \ \ \beta E_{R, y_{+1}|R_{-1}, y}\ v(y_{+1}, s, b, R). \tag{2}$$

Here, $u(con)$ is the utility from non-durable consumption con, which is of the CRRA form:

$$u(con) = \frac{1}{1-\gamma} con^{1-\gamma}. \tag{3}$$

Some existing research on household finance (e.g., Gomes and Michaelides (2008)) uses the recursive utility framework of Epstein and Zin (1989) instead of the CRRA framework. The advantage of the recursive utility framework is the separation of the elasticity of intertemporal substitution (EIS) from risk aversion, which is important when fitting the equity premium. Since our goal is not to explain the equity premium, we maintain the CRRA framework to keep the model simple. We note that even in our model, the inverse of the EIS is not the curvature of the CRRA utility function because we allow for portfolio adjustment costs (Bonaparte, Cooper, and Zhu 2012). For similar reasons, Fagereng, Gottlieb, and Guiso (2017) also use the CRRA utility function.

4.1.2 Consumption Under Portfolio Adjustment

The investor can either privately manage his investments or delegate that task to an investment manager. This choice affects his overall consumption level. When he privately manages his investments, his consumption is con_{pm}. When he delegates that task to an adviser, his consumption is con_d. Therefore, his consumption con is given by the following budget constraint:

$$con = Max\ (con_{pm},\ con_d), \tag{4}$$

where

$$con_{pm} = R_{-1}s_{-1} + rb_{-1} - s - b + y \times \Psi - FC - C, \tag{5}$$

and

$$con_d = R_{-1}s_{-1} + rb_{-1} - FC - C - s \times (1 - DF). \tag{6}$$

Equations (4) to (6) indicate that consumption is affected by wealth, asset returns, income, and various costs related to investing in the risky asset. The costs of owning and trading equity are determined by the parameters FC, C, Ψ, and DF, which we describe next.

4.1.3 Costs of Stock Ownership and Trading

Following the portfolio choice literature, we consider three types of costs that investors may face (Vissing-Jørgensen 2002b). First, investors face fixed costs FC to owning equity. These fixed costs represent the on-going costs of maintaining a trading account that are paid even if the investor does not trade. We allow for this type of fixed costs for completeness since most models in the limited market participation literature include some form of fixed costs to owning stocks (Luttmer 1999; Paiella 2001; Gomes and Michaelides 2008). To keep the estimation simple, we set FC to 0.020 consumption units, which is very small.[15]

Second, the investor pays transaction costs C, which capture trading costs such as commissions, fees, and other costs related to trading like the bid-ask spread (Vissing-Jorgensen 2004). As in Heaton and Lucas (1996), the trading costs C are proportional to the change in the value of the risky asset holdings. That is, they depend on the difference between s_{-1} and s. The functional form for the proportional trading costs C is shown in Section 4.2.1.

Third, the investor incurs costs related to managing her investments. If the investor privately manages his investments, he suffers an opportunity cost related to lost income. The lost income is $y \times (1 - \Psi)$, $\Psi < 1$, and affects consumption through a reduction in income. We interpret $(1 - \Psi)$ as a per-period cost, which captures the cost of information gathering, analysis, trading, and time spent on taxes for direct stockholders (Dumas and Luciano 1991; Vissing-Jorgensen 2004).

We model the time cost of self portfolio management as lost income, following Gomes and Michaelides (2005) and Alan (2006). These earlier studies examine the long-term decision to own stocks and not the dynamic short-term decision to enter/exit the stock market. Consequently, they set the time cost as a portion of permanent income, which represents the long-term earnings of the investor. Because our focus is on the dynamic decision to own

[15] In unreported results, we find that setting FC to 0.020 consumption units results in the best model fit. This corresponds to about \$142 per year and is consistent with existing evidence that fixed-type costs to stock ownership are very low. For instance, using a different methodology, Paiella (2007) finds that the lower bound of fixed costs that can rationalize lack of market participation is \$130 per year.

stocks, it is more appropriate to model the time cost as a portion of current income.

Finally, if the investor decides to delegate her investment decisions, she pays a delegation/management fee DF. We follow Wu, Wermers, and Zechner (2016) and set DF to 1% of the portfolio value at the end of the period (s). Specifically, Table 1 of Wu, Wermers, and Zechner (2016) reports that, on average, the management fee is 0.939% and 1.007% of assets under management for funds focusing on domestic and international equities, respectively. The average of these estimates is about 1%, which we use in our analysis.

The choice of a 1% management fee is also in line with Wermers (2000), who finds that the average expense ratio of active mutual funds (weighted by total net assets of funds) is around 0.93% over the 1990-1994 period. We allow for the delegation of investment decisions to ensure that the costs faced by investors for portfolio management are not unreasonably high and never exceed the 1% of the value of their risky investment account.

4.1.4 Value Function Under No Portfolio Adjustment

If the investor chooses not to rebalance, then his value function v^n is:

$$v^n(y, s_{-1}, b_{-1}, R_{-1}) \quad = \quad max_{b \geq \bar{b}} \;\; u(y + rb_{-1} - b) \quad + \quad \beta E_{R,y+1|R_{-1},y} \;\; v(y_{-1}, s, b, R). \tag{7}$$

In this case, the stockholder consumes only his labor income plus the cash payouts for his riskless asset holdings. For simplicity, we assume that the risky asset return is entirely based on capital gains (i.e., no cash dividends are paid out). With no rebalancing, the proceeds from the existing stock portfolio are costlessly reinvested. Hence, the portfolio value at the end of the period is given by: $s = R_{-1}s_{-1}$.

4.2 Pre-estimated Parameters

In Section 5, we solve and estimate the model at the quarterly frequency. However, we are forced to pre-estimate some model components because portfolio choice models with stochastic income have many decision and state variables that make them difficult to solve and estimate. In this section, we present the estimates of those pre-estimated processes.

4.2.1 Proportional Trading Costs

We pre-estimate the proportional trading costs using actual transaction-level trading data. In the model, there is only one risky asset. Since investors trade multiple assets in our dataset, the specification of C we estimate is based on multiple assets. After the estimation, we use the multiple-asset empirical specification in our single-asset model specification.

In the estimation, we assume that the cost function C depends on the change in asset holdings of each asset i (i.e., $s^i_{-1} - s^i$). For simplicity, C is separable across assets and it differs between sales and purchases:

$$C = \sum_i C^j(s^i_{-1}, s^i), \tag{8}$$

where $j = b$ for assets i being bought and $j = s$ for assets being sold. When the stockholder buys asset i, that is $s^i \geq s^i_{-1}$, the functional form for the proportional trading costs follows a quadratic specification given by:

$$C^b(s^i_{-1}, s^i) = v^b_0 + v^b_1(s^i_{-1} - s^i) + v^b_2(s^i_{-1} - s^i)^2. \tag{9}$$

Similarly, when the stockholder sells asset i, the the proportional trading costs are:

$$C^s(s^i_{-1}, s^i) = v^s_0 + v^s_1(s^i_{-1} - s^i) + v^s_2(s^i_{-1} - s^i)^2. \tag{10}$$

To ensure that the trading costs are consistent with what investors face, we adopt the approach of Bonaparte, Cooper, and Zhu (2012) and estimate equations (9) and (10) with monthly stockholder trading data. Specifically, we use the Barber and Odean (2000) data that include information on trades of common stocks of about 78,000 stockholders who were clients at a discount brokerage house from January 1991 to December 1996. If a stockholder bought different stocks in a given month, the stockholder reports the commission, quantity, and price for each one of these stocks separately. Based on this data, we compute total trading costs. They include direct costs such as brokerage fees and commissions, opportunity costs of trading from unfilled or partially filled limit orders, and the bid-ask spread.

We estimate the trading cost equations (9) and (10) with ordinary least squares (OLS). In the regressions, the dependent variable is the total transaction costs of each trade. The independent variables are the trade value (i.e., the price of the shares times the number of shares), the trade value squared, and a constant. We report the results in Appendix A.4. The estimated transaction equations (9) and (10) are directly imputed into the model.

The OLS estimation suggests that the average cost of trading, captured by the constant in the regressions, is about $56 for buying and $61 for selling. The estimates of the linear and quadratic terms are also important. To get a sense of magnitudes, the average purchase (sale) in our sample has a value of about $11,000 ($13,372), and thus, the cost of this trade is about $70 ($80). For trades of this size, the impact of the quadratic term is small.

We acknowledge that these trading costs might appear high since they are estimated using data from the '90s. Since then, trading costs have been declining (Bogan 2008). Nevertheless, as we show in Section 5.5, the proportional trading costs do not drive the main results of the model. We include them in the model because investors are still exposed to the bid-ask spread even if the commissions and fees for trading are low.

4.2.2 Asset Return Processes

We also impute the processes for assets. In the model, we allow for two assets: a riskless asset and a risky asset. The return of the riskless asset is 0.25% quarterly. This value is in line with Mehra and Prescott (1985).

We model the risky return following Bonaparte, Cooper, and Zhu (2012). Like them, we assume that the risky return process is IID and it has three states, which occur with equal probabilities (33.3% each).[16] As in Bonaparte, Cooper, and Zhu (2012), the return of the neutral/middle state is 2.12% and the return of the good (bad) state is 2.12% plus (minus) one half of 7.84%. These numbers are, respectively, the quarterly mean return and standard deviation of the real returns of the S&P500 index for the 1947-2007 period.[17]

[16] In unreported results, we find that adding more return states does not change the results significantly. To keep the model simple, we only include three states in the main analysis.

[17] These data are available at http://www.econ.yale.edu/~shiller/data.html. We choose the 1947-2007 time period as it is similar to the sample periods of other data sets used in our analysis.

4.2.3 Income Process

Finally, we pre-estimate the income process. In general, the estimation of household income processes is difficult (e.g., Guvenen (2007), and Browning, Ejrnaes, and Alvarez (2010)). Therefore, we choose a simple empirical model that can capture the evolution of household income reasonably well (Viceira 2001; Campbell, Cocco, Gomes, and Maenhout 2001; Gourinchas and Parker 2002; Gomes and Michaelides 2005; Gomes and Michaelides 2008).

Specifically, following Campbell, Cocco, Gomes, and Maenhout (2001), we decompose household income y into two components:

$$y_{i,t} = \tau Z_{i,t} + A_{i,t}. \tag{11}$$

Here, $y_{i,t}$ is labor income for household i at period t. $\tau Z_{i,t}$ is the deterministic component of income, where $Z_{i,t}$ is a vector of household demographic variables like age, and τ is the corresponding vector of coefficients. $A_{i,t}$ is the stochastic component of income, which is persistent and follows the process $A_{i,t} = \rho A_{i,t-1} + \epsilon_{i,t}$. $\epsilon_{i,t}$ is a transitory shock.

We estimate the income model using the annual income data provided by the PSID. The details of the estimation are presented in Appendix A.3. Given that we simulate and estimate our model at the quarterly frequency, we translate the estimated annual income process in (11) into the quarterly frequency using the methodology of Tauchen and Hussey (1991). Then, we transform the quarterly income process into a five-state Markov chain following Tauchen (1986). We impute the Markov chain into our model and its estimation.

5 Model Estimation

In this section, we present the model estimation using the simulated method of moments (SMM). The SMM provides estimates for the coefficient of relative risk aversion (γ), the discount factor (β), and the portion of income lost due to portfolio management (Ψ).

5.1 Data Moments

We use 12 data moments in our estimation.

5.1.1 Ownership and Account Management Moments

Our first moments are related to the ownership of non-retirement accounts. The first one is the probability of participating in non-retirement accounts, conditional on having participated in the recent past. We extract this moment from probit regressions estimated with the PSID and SCF data. In these regressions the dependent variable is a dummy variable related to the current ownership status and the key independent variable is the ownership status in the previous wave.[18] In unreported results, we find that across the PSID and the SCF estimations, the average estimate of the past-participation variable is 0.51, which is the moments we match in the SMM.

The second moment is the stock ownership turnover related to the short-term decision to own stocks. We capture ownership turnover using the sum of the average entry and exit rates from non-retirement accounts. Based on the PSID statistics in Panel A of Table 1, the mean entry and exit rates between two consecutive waves are 7.3% and 8.7%, respectively. These estimates imply that the average turnover is 16% (= 7.3% + 8.7%).[19]

The third moment is related to the fraction of households that always participate and invest in risky assets. This moment enables us to capture the long-term decision to own stocks. We set this fraction to 32.8%, which is the portion of stockholders in the PSID that participated in non-retirement accounts in all 12 waves (see Table 1, Panel B, Column 3).

The fourth moment is the average market participation rate. We set this rate to 48.9%, which is the average participation rate in non-retirement accounts in six SCF waves (see Table 2, Panel B). This statistic is in line with Grinblatt, Keloharju, and Linnainmaa (2011), who document that about 50% of U.S. households own stocks in non-retirement accounts.

[18]The other independent variables are age, education, income, wealth, male and white.

[19]In unreported results, we find similar results if we separate the entry and exit moments. To keep the number of moments small in our main analysis, we simply match their sum.

The fifth moment is the rebalancing rate of the risky equity share. This moment helps us identify the time-costs of portfolio management captured by Ψ. The rebalancing rate is the cross-sectional average of a trading indicator. The trading indicator takes the value of one if the household has changed its asset holdings in a given period and zero otherwise. We use the estimate of the rebalancing rate from the PSID. Specifically, in Table 1, Panel C, we show that the average rebalancing rate in non-retirement accounts is 48.6%.

The last moment is related to the decision to self-manage or delegate portfolio rebalancing. In particular, we use the 2016 SCF wave, where we find that 64.2% of households choose to delegate their portfolio decisions. This statistic is similar in other waves.

5.1.2 Wealth Ratio Moments

We use three moments related to wealth. For stockholders, we use the average equity share (i.e., the ratio of median stockholdings in non-retirement accounts and median wealth), and the ratio of median financial wealth to median wages. For all households (i.e., both stockholders and non-stockholders), we use the ratio of median financial wealth to median wages. We obtain these statistics from the SCF waves from 1989 to 2010. The statistics for stockholders are in Table 2, Panel E.1, and statistics for all households are in Panel E.2.

Based on these statistics, we set the stockholders' average equity share to 0.413 and their average wealth-to-wages ratio to 1.034. For the group of all households, we set the average wealth-to-wages ratio to 0.425. We use the SCF for these moments as the SCF wealth data is known to be more precise than the wealth data reported in the PSID.

5.1.3 Aggregate Consumption Moments

We also use aggregate-level moments that capture the sensitivity of aggregate consumption growth to stock market returns. We include aggregate moments to ensure that the aggregate implications of the model are realistic. Specifically, Addoum, Delikouras, and Korniotis (2018) show that consumption and portfolio decisions are interrelated. Consequently, how aggregate consumption reacts to stock-market changes should be associated with the trading decisions of households whose goal is to smooth consumption by hedging income shocks.

To obtain the aggregate consumption moments, we estimate the log-linear approximation of a consumption Euler equation of Hansen and Singleton (1983). This approximation leads to a linear equation of the log of consumption growth (Δc) on the log market return:

$$\Delta c_{t+1} = \alpha_0 + \alpha_1 \times \log(R_{t+1}). \tag{12}$$

We offer no structural interpretation of the parameter α_1. We interpret it as an empirical moment and call it the aggregate elasticity of intertemporal substitution (EIS).

We estimate equation (12) with ordinary least squares using the non-durable consumption data of stockholders from Malloy, Moskowitz, and Vissing-Jørgensen (2009). The data are quarterly, covering the period from March 1982 to November 2004. For the return data, we use the quarterly return for the S&P500. We also estimate equation (12) with consumption growth rates 1, 4, and 16 quarters ahead. We use different horizons to examine if the impact of trading costs is less important in the long run. In untabulated results, we find that the EIS for 1, 4, and 16 quarters ahead are 0.0295, 0.1269, and 0.3518, respectively. We label these estimates as "1-quarter α_1," "8-quarter α_1," and "16-quarter α_1," respectively.

5.2 Simulated Method of Moments Estimation Method

We estimate the model with simulated methods of moments. The SMM finds the value of the parameters γ, Ψ, and β that minimize the following quadratic form:

$$\prod = min_{(\gamma,\Psi,\beta)}(M^s - M^d)'W(M^s - M^d). \tag{13}$$

Here, M^d are the moments from the data and M^s are the simulated values of those moments for a given set of parameters. The matrix W is an identity matrix. We are unable to use the optimal weighting matrix, which is usually the Newey-West (1987) covariance matrix of the data moments. We face this constraint because the moments in M^d are from different data sets and we are unable to calculate covariances of moments from different sources that correspond to different types of households. For instance, the moments related to the stock shares from SCF are based on a subsample of stockholders. In contrast, the participation rates and wealth/income ratios are from a sample that includes non-participants and participants.

To apply the SMM estimation, we solve the dynamic programming problem of investors at the quarterly frequency. Specifically, we solve the model with value function iteration and create a panel data set with 500 households and 800 quarters. We then compute moments from the simulated quarterly data in a way that matches the frequencies of the moments from the actual data, which vary from quarterly to bi-annual.[20] The estimation exercise finds the values of γ, Ψ, and β that bring these simulated moments as close as possible to the actual data moments. See Appendix A.5 for more details about the simulation.

5.3 Parameter Estimates

We report our main model estimation results in Panels A and B of Table 6. The results in Panel A indicate that the estimated coefficient of relative risk aversion (CRRA) is 3.087. This is a reasonable estimate and consistent with existing findings. For example, Cagetti (2003) matches wealth data and reports CRRA estimates between 2.74 and 4.26. As Alan (2006) notes, studies that match consumption data report lower CRRA. In particular, Attanasio, Banks, Meghir, and Weber (1999) estimate CRRA to be around 1.5, while Gourinchas and Parker (2002) report an estimate between 0.28 and 2.29.

Our discount factor estimate is 0.970. This estimate is also in line with existing findings in the literature. In particular, Alan (2006) finds the discount factor to be about 0.86, while Gourinchas and Parker (2002) report an estimate of about 0.96.

The time cost to portfolio management is 1.20% of income ($= 1 - 0.988$, since $\Psi = 0.988$). This estimate implies that an investor with an annual income of \$72,000 will have to sacrifice about \$864 (= \$72,000 $\times$ 1.20) per year in income if he chooses to exclusively self-manage

[20]For example, the turnover PSID statistics in Panel A of Table 1 are based on entries and exits from non-retirement accounts between bi-annual waves. Therefore, with the simulated data, we compute the turnover rate with the entries over eight quarters (i.e., the number of new stockholders over an eight-quarter period that are not stockholders in the previous eight quarters) and the exits over eight quarters (i.e., the number of households that sell all their equity holdings over an eight-quarter period but owned equity in all the previous eight quarters).

his portfolio.[21] In general, a household will be indifferent between self-management and delegation if $y \times (1 - \Psi) = s \times DF$ or if the equity-to-income ratio (s/y) is equal to 1.20 (= $(1-\Psi)/DF = 0.012/0.01$). As a result, in the model, households with large portfolios relative to their income will choose to self-manage, and those with relatively smaller portfolios will choose to delegate.[22]

In the estimation, we also compute the precision of our estimates. In particular, we estimate the standard errors following the methods of Adda and Cooper (2003). Based on these standard errors, we find that all our parameter estimates are statistically significant.

5.4 Model Fit and Implied Moments

We assess the empirical fit of the model using the J-test of over-identifying restrictions, which we report in Panel A. We find that the J-statistic is 0.111 and the corresponding p-value is about 0.010. Thus, statistically, the model cannot be rejected.

The good model fit suggests that the empirical moments and those implied by the model are close. As shown in Panel B of Table 6, the model captures the average persistence in stock ownership relatively well, which is 0.510 in the data and 0.493 in the model. Moreover, the rebalancing rate in the model (= 0.522) is close to the rate observed in the data (= 0.486). The model predicts slightly higher turnover in stock ownership relative to the data. In particular, the average entry plus exit rates in the model is 0.240, but only 0.160 in the data. This finding is not surprising since, in the model, households can only trade one risky asset to mitigate income and return shocks.

Examining the wealth-related moments, we find that the median financial wealth to wages for stockholders is higher in the data (1.034) than in the model (0.886). Further,

[21] The income of $72,000 is the average annual income in the PSID sample we use to estimate the imputed income process in the model. See Section A.3 of the Appendix.

[22] As noted, the model implies a negative relation between the ratio s/y and the probability of delegating portfolio decisions. In unreported results, we validate this implication using data from the 2016 SCF. We estimate a probit regression of the delegation dummy variable on the equity wealth-to-income ratio. The control variables are gender, race, age, years of schooling, and income. The regression indicates that among investors with non-retirement accounts, the probability of delegating is negatively and statistically related to the equity wealth-to-income ratio.

upon participation in the market, the households in the model invest more in the risky asset than in the data (average equity share in the data is 0.413 and 0.694 in the model). As discussed in Section 5.6.2, we can better capture these wealth moments and the average equity share when we introduce a stock market crash.

In terms of the aggregate consumption-return moments, the model does well in fitting the one-quarter consumption sensitivity. The model-implied 4 and 16 quarters consumption sensitivities monotonically increase, like the empirical sensitivities. However, they are lower than the empirical sensitivity levels.

5.5 Changes in the Costs of Equity Ownership and Trading

Next, we examine which type of costs faced by investors are the most important for the dynamic decision to own stocks. For this analysis, we report how the model-implied moments respond to changes in one or more of the cost components of owning and trading the risky asset. Specifically, we use the estimates of the preference parameters from Table 6 and simulate the model by shutting off some cost components. We report the implied moments from these new simulations in Table 7. To summarize the fit of each simulation, we report its mean squared error (MSE) scaled by 100. For reference, in Columns (1) and (2) of Table 7, we report the data moments and the moments of the baseline estimation, respectively.

The results in Table 7 show that costs are important. However, not all cost components are equally significant. Specifically, we see in Column (3) that when we set all costs to zero, the model performance deteriorates. The MSE increases from 14.29 for the baseline estimation to 37.85, which indicates that equity ownership and trading costs are needed to fit the dynamic decision to own stocks.

We sequentially introduce the various forms of costs to examine how they affect the moments implied by the model. First, we only allow for fixed-type costs of owning stocks. We find that such costs do not improve the fit of the model. As we see in Column (4), the MSE from the model simulation is still high (= 37.85).

The model moments get closer to the data moments when we introduce the costs related to portfolio management. As we see in Column (5), the MSE drops to 14.58, which is almost identical to the MSE of the baseline estimation (= 14.29). The model moments diverge from the data moments when we eliminate the portfolio management costs and imposing fixed ownership and trading costs. The MSE of the model increases to 36.42 (see Column (6)). In sum, the results in Table 7 suggest that portfolio self-management costs are the most important determinant of the dynamic stock ownership decisions.

5.6 Changes in the Risk Environment

In the last part of our analysis, we use our simulation results to examine how households react when the risks they face change. We focus on income risk because it is the main source of household-level idiosyncratic risk exposure in the model. We also focus on equity risk because it is the most important source of aggregate risk in our model.

For this analysis, we again use the estimates of the preference parameters from Table 6 and simulate the model by increasing either idiosyncratic income risk or return risk. In Table 8, we report the implied moments from these simulations. As before, to summarize the fit of each simulation, we report its mean squared error (MSE) scaled by 100. For reference, in Columns (1) and (2) of Table 8, we report the data moments and the moments of the baseline estimation, respectively.

5.6.1 Higher Income Risk

For the income risk analysis, we run a simulation where the impact of idiosyncratic income shocks is magnified by 25%. Specifically, in our model, the stochastic component of income (A) is affected by the transitory shock ϵ. To amplify income risk, we multiply ϵ by 1.25. We then obtain a new five-state Markov chain and use it in the new simulation.

We report the new model-implied moments in Column (3) of Table 8. The most important finding is that the model-implied ownership turnover is now 0.291, which is higher than the turnover rate from the baseline estimation (0.240). This result confirms our conjecture that income risk is important for stock ownership turnover and the higher the income risk. It also confirms our empirical finding that in the cross-section of PSID households, those with higher income risk have higher turnover rates.

The new model has a few weaknesses. Compared to the data, it implies high levels of stock ownership and wealth accumulation. In particular, the average stock market participation rate is 70.9% compared to 65.7% in the baseline simulation. Also, the rebalancing rate of the equity share increases to 60.9% from 52.2%. The average equity share (= 0.701) and the financial-wealth-to-wages ratios are also high. These results are not surprising since in canonical models of portfolio choice, higher income risk stimulates more precautionary savings and higher wealth accumulation. But with higher wealth, the household needs to exit the stock-market less often to insulate consumption from income risk. Overall, the counterfactual stock ownership and wealth accumulation inflates the MSE of the model to 25.52, which is much higher than the MSE of the baseline model (14.29).

5.6.2 Stock Market Crash Risk

We examine the impact of equity risk on portfolio decision with a stock market crash. Fagereng, Gottlieb, and Guiso (2017) also consider a stock-market crash in their model. The crash is introduced by modifying the process of the risky return. In the baseline model, the risky return has three states (i.e., bad, neutral, good). We do not change the probabilities and outcomes of the good and neutral states. However, we decompose the bad state into two states. One of them is a crash, which is set to happen with a probability 5% and has an annualized return of −25%. We obtain these numbers from Table 1 in Barro and Ursúa (2017). They report that during a period of 139 years (1889 to 2006), there were seven stock market crashes in which the cumulative real return of the stock market was −25% or lower.

We report the new model-implied moments in Column (4) of Table 8. We find that higher stock market risk almost has no impact on the ownership turnover. In particular, the model implied turnover rate is identical (at the third decimal place) to the rate implied by the baseline estimation. However, the model with the stock market crash fits the wealth moments better. For example, its average equity share is 0.445, which is closer to the equity share in the data (0.413) than the average equity share in the baseline simulation (0.694). Moreover, the model with the crash fits very well the moments related to the portion of investors who delegate their investments and the rebalancing rates of stockholders. The MSE of the high-stock-market-risk simulation is 10.38, which is very close to the MSE of the baseline estimation (= 14.29).

Taken together, the results from the alternative models indicate that household idiosyncratic income risk is more important than aggregate stock market risk for ownership. The results also suggest that expanding the baseline model to include a more realistic equity return process can help in fitting the overall wealth accumulation of investors. Other potential extensions include adding housing to the model (Chetty, Sándor, and Szeidl 2017) or life-cycle considerations like retirement. In our baseline analysis, we abstract from these very interesting extensions to examine how far we can go with a simple portfolio choice model. We find that for ownership turnover, the baseline model performs very well.

6 Summary and Conclusions

This study examines household ownership turnover in non-retirement accounts. Our key conjecture is that income shocks generate significant equity ownership turnover. We find both empirical and theoretical support for this conjecture. In our empirical analysis, we use data from multiple sources to show that households with high income risk enter and exit non-retirement investment accounts frequently. Further, households that experience a decrease in labor income have a higher chance of exiting non-retirement investment accounts. We exclude retirement account from our analysis because turnover in retirement accounts is very low.

To interpret these empirical results, we develop a portfolio choice model with borrowing constraints, short-sale constraints, income shocks, and costs to equity ownership and trading. We estimate the model and find that it can fit many moments related to ownership and trading decisions in non-retirement accounts. Among the various costs we consider, the cost related to portfolio self-management is the most important factor in fitting the entry/exit moments. Surprisingly, we find that idiosyncratic income shocks affect ownership turnover more than exposure to higher equity risk.

These results contribute to the asset pricing literature that focuses on the behavior of stockholders. Many asset pricing studies assume that when investors enter the stock market, they almost never exit. Based on this assumption, existing studies use factors related to consumption of stockholders and define marginal investors as those who own stocks in a particular period, ignoring their ownership history (Mankiw and Zeldes 1991; Vissing-Jørgensen 2002a; Brav, Constantinides, and Geczy 2002). However, Malloy, Moskowitz, and Vissing-Jørgensen (2009) demonstrate that long-run consumption risk of stockholders is an important factor in fitting the cross-section of expected returns. In light of the importance of long-run risks, our results imply that it is more appropriate to focus on the consumption growth risk of stockholders with a long history of stock ownership.

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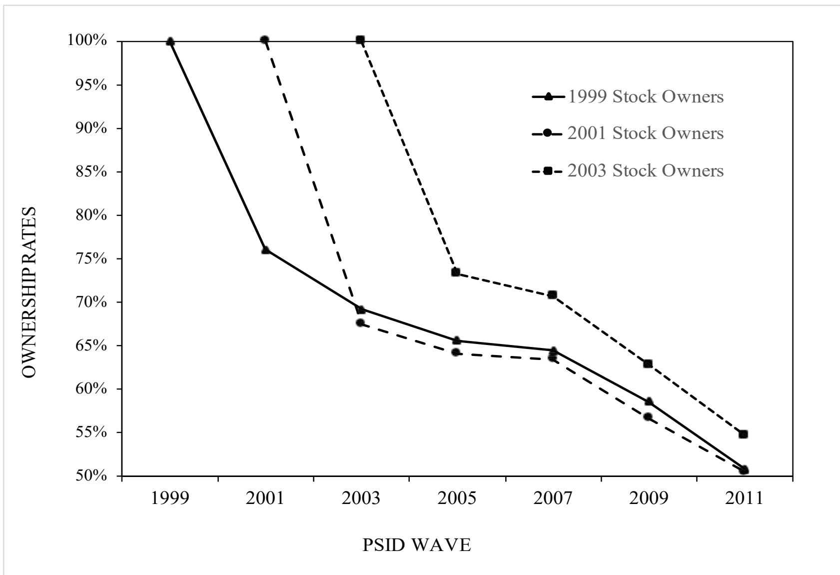
Figure 1: Ownership History of PSID Stockholders

This figure depicts the ownership history of different cohort of stockholders. We identify stock holders in a particular wave of the PSID and plot the fraction of these stockholders who own stocks in any of future waves. In Panel A, we focus on the cohort of stock owners in the 1999, 2001, and 2003 PSID waves. In Panel B, we present the ownership history of three cohorts of households who owned stocks in 1999, which are, all the stock owners, those with stock holdings less than $300 in 1999, and those with stock holdings of at least $300 in 1999.

Panel A: Ownership History of of Stockholder as of 1999, 2001, and 2003



Panel B: Ownership of 1999 Stockholders based on Stock Holdings on 1999

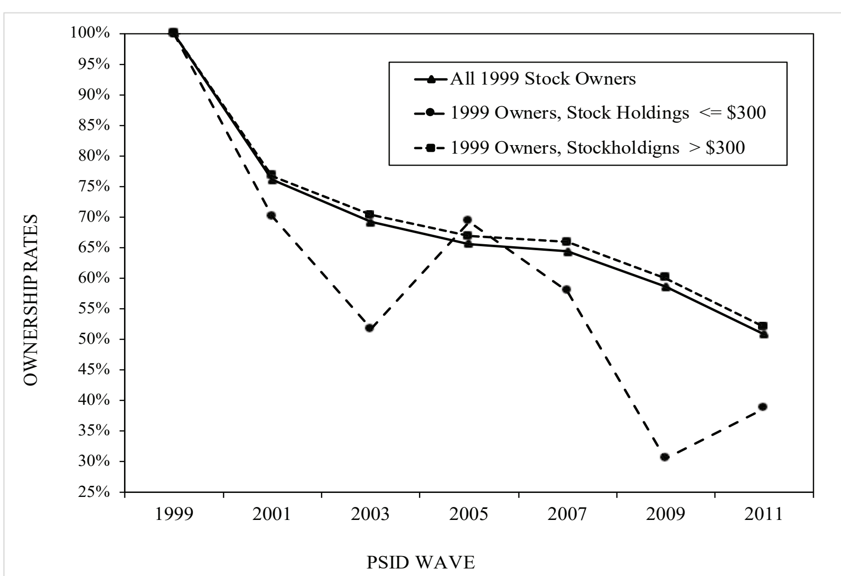


Table 1: Ownership Turnover in Non-Retirement Accounts: PSID, 1999-2011

This table reports entry and exit statistics using seven waves (1999, 2001, 2003, 2005, 2007, 2009 and 2011) of the Panel Study of Income Dynamics (PSID). Panel A reports entry and exit statistics for ownership in non-retirement accounts. Column (1) reports the ownership rates in non-retirement accounts. Column (2) reports the fraction of new owners in year $t+2$, that is, the fraction of households that did not invest in non-retirement accounts in year t but invested (entered) in the following year $t+2$ as a fraction of all households. Column (3) reports the fraction of households that own non-retirement accounts in year t but became new non-owners (exited) in the year $t+2$ as a fraction of all households. Column (4) reports the fraction of non-owners in year t that enter non-retirement accounts in year $t+2$ as fraction of all owners in year t. Column (5) reports the fraction of owners in year t that exit (sell their holdings in non-retirement accounts) in year $t+2$ as a fraction of all owners in year t. Panel B reports the entry and exit statistics for the baseline cohort of stockholders: owners of non-retirement accounts in the 1999 wave. Column (1) reports the fraction of this baseline cohort who participate in non-retirement accounts in any of the future waves. Column (2) reports the fraction of 1999 owners who exit non-retirement accounts in a particular wave. Column (3) reports the fraction of the baseline owners in year t who participated in non-retirement accounts in each of the previous waves. Column (4) reports the fraction of baseline owners who re-enter non-retirement accounts after having exited in a previous wave. Panel C reports the portfolio rebalancing rates for owners of non-retirement accounts. Specifically, we present the average of the trading indicator across households by year.

Panel A: Entry and Exit Statistics: PSID 1999 Cohort

	(1)	(2)	(3)	(4)	(5)
	Ownership	% of All Households$_t$		% of Stockholders$_t$	
Wave	Rate	Entry$_{t+2}$	Exit$_{t+2}$	Entry$_{t+2}$	Exit$_{t+2}$
1999	31.3%	-	-	-	-
2001	33.5%	9.7%	7.5%	30.9%	23.9%
2003	30.8%	7.2%	9.9%	21.5%	29.6%
2005	29.7%	7.2%	8.3%	23.4%	27.0%
2007	29.7%	7.2%	7.2%	24.3%	24.3%
2009	27.5%	6.3%	8.6%	21.3%	28.9%
2011	22.6%	5.9%	10.8%	21.6%	39.3%
Average	29.3%	7.3%	8.7%	23.8%	28.8%

Table 1: Ownership Turnover, PSID, 1999-2011 – Cont'd

Panel B: Tracking the Owners: 1999 Wave

Wave	(1) Ownership Rates of 1999 Owners in Future Waves	(2) Exit of 1999 Owners	(3) 1999 Owners who Own Non-Ret A/c in Previous Waves	(4) 1999 Owners who Exited and Re-entered
1999	100.0%	-	100.0%	-
2001	76.1%	23.9%	76.1%	-
2003	69.2%	6.9%	59.8%	39.2%
2005	65.6%	3.6%	50.5%	18.6%
2007	64.4%	1.2%	45.5%	19.3%
2009	58.6%	5.8%	40.3%	14.8%
2011	50.8%	7.8%	32.8%	4.5%

Panel C: Average Trading Levels

	Year							
	1999	2001	2003	2005	2007	2009	2011	Average
% Trading	-	0.561	0.480	0.510	0.476	0.429	0.462	0.486

Table 2: Summary Statistics from Survey of Consumer Finances

This table reports statistics computed using the Survey of Consumer Finances (SCF) data. We use the waves of the triennial SCF from 1995, 1998, 2001, 2004, 2007, and 2010. We also use the SCF panel for the years 2007 and 2009. By stockholder (non-stockholder), we refer to households that have some (zero) wealth in non-retirement investment accounts. Panel A reports the statistics for entry and exit in non-retirement accounts using the SCF 2007-2009 panel. Specifically, we report the ownership statuses ("Own" and "Not Own") over the two years. Panel B reports the household participation rate in non-retirement accounts for the survey years from 1995 to 2010. Panel C reports summary statistics of wage and equity for the years 2007 and 2009. Specifically, for each sample examined, the columns report the mean and median of equity and wage in 2007 and 2009. The samples include "All households"; those who own equity in non-retirement accounts in the year 2009 ("Stockholders 09"); those who own equity in non-retirement accounts in the year 2007 ("Stockholders 07"); those who enter investing in non-retirement accounts in the year 2009 but were not investors in 2007 ("Entering Stockholders"); and finally, those who did not invest in non-retirement accounts (equity=0) in the year 2009, but did invest in 2007 (equity>0), (Exiting Stockholders"). Panel D focuses on households that exit non-retirement accounts (stockholders in 2007 and not 2009) and those who enter investing in non-retirement accounts (stockholders in 2009 but not 2007). The column labeled "Averages" reports the average stockholdings for exiting or entering households. The column labeled "% of 09 equity" reports the average stockholding as a percentage of average equity held by all stockholders in 2009. The column labeled "% of average 09 earnings" reports average stockholdings as a percentage of average labor earnings of stockholders in 2009. Panel E reports ratios of stock holdings in non-retirement accounts, wealth, and wage, where the top row labeled "Survey year" reports the survey year. Panel E.1 reports statistics for households with wealth in non-retirement accounts, where the first row labeled "Equity share" reports the median stock holdings divided by financial wealth. The second row labeled "Median of Fin. Wealth to Wages (Stockholders)" reports the median of financial wealth divided by wage. Panel E.2 reports statistics for all households (stockholder and non-stockholder), where the first row labeled "Median of Fin. Wealth to Wages (All households)" reports the median wealth to wage ratio for all households.

Panel A: Entry and Exit - 2007-09 SCF Waves

Year/Year:	2009	
2007	Not Own	Own
Not Own	37.1%	9.3%
Own	7.4%	46.2%

Panel B: Participation Rates - 1995 to 2010 SCF Triennial Waves

	Year						
	1995	1998	2001	2004	2007	2010	Average
Part. Rate	0.411	0.489	0.522	0.502	0.511	0.499	0.489

Table 2: Summary Statistics from Survey of Consumer Finances – Cont'd

Panel C: Wage and Equity in Non-Retirement Accounts - 2007-09 SCF Panel										
	All Households		Stockholders 09		Stockholders 07		Entering Stockholders		Exiting Stockholders	
Measure	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
2007 Equity	$124,287	932	217,048	25,890	231,641	36,246	.	.	51,824	9,320
2007 Wage	$55,512	34,079	79,765	56,444	81,202	57,509	43,888	34,079	45,425	30,884
2009 Equity	$87,771	1,500	158,189	27,500	159,721	25,000	22,350	5,000	.	.
2009 Wage	$53,932	32,875	77,846	58,776	77,638	57,780	47,856	37,856	38,991	25,901
Panel D: Exit and Entry Volume in Non-Retirement Accounts - 2007-09 SCF Panel										
Status	Average Ownership		% of Average 2009 Equity		% of Average 2009 Earnings					
Exit	$51,824		32.8%		66.6%					
Entry	$22,350		14.1%		28.7%					
Panel E: Financial Wealth and Wage - SCF Triennial Waves										
	Survey Year									
	1989	1992	1995	1998	2001	2004	2007	2010		Average
Panel E.1: Wealth Shares for Household with Non-Retirement Accounts (i.e., Stockholders)										
Stock/Fin	0.27	0.32	0.41	0.48	0.51	0.46	0.44	0.40		0.41
Fin/Wage	0.79	0.88	0.86	1.06	1.14	1.20	1.20	1.14		1.03
Panel E.2: Median Financial Assets by Wage, All Households										
Fin/Wage	0.29	0.30	0.37	0.50	0.53	0.47	0.54	0.40		0.42

Table 3: Cross-sectional Determinants of Entry and Exit into Non-Retirement Accounts

This table reports estimates from cross-sectional regressions. Panel A shows summary statistics of the variables in the regressions and Panel B reports the regression results. The dependent variables in Regressions (1),(2), and (3) are the log of 1 plus the total number of entries, exits, and entries and/or exits, respectively. In Regressions (4), (5), and (6), the dependent variables are dummy variables that take the value of 1 if, over the sample period, the household had at least one entry, one exit, and one entry or exit, respectively. We estimate Regressions (1) to (3) with ordinary least squares. The t-statistics, based on robust standard errors, are in parenthesis underneath the coefficient estimates. We estimate Regressions (4) to (6) with a probit estimator and report the respective marginal effects. The z-statistics are based on robust standard errors. The data are from the 1999 to 2011 PSID waves. The independent variables are average income, average wealth (i.e., net worth), and income risk, computed as the standard deviation of biennial income growth between 1999 to 2011. The control variables are age, race, gender, and education, as of 2011.

Panel A: Summary Statistics

			Percentile					
	Mean	SD	P10	P25	Median	P75	P90	N
Log (1 + Entry)	0.522	0.399	0	0	0.693	0.693	1.099	4,085
Log (1 + Exit)	0.605	0.389	0	0	0.693	0.693	1.099	4,085
Log (1 + Entries/Exits)	0.907	0.51	0	0.693	1.099	1.099	1.609	4,085
Entries	0.819	0.693	0	0	1	1	2	4,085
Exits	0.964	0.702	0	0	1	1	2	4,085
Entries and Exits	1.783	1.254	0	1	2	2	4	4,085
I(Entries>0)	0.665	0.472	0	0	1	1	1	4,085
I(Exits>0)	0.747	0.435	0	0	1	1	1	4,085
I(Entries/Exits>0)	0.821	0.383	0	1	1	1	1	4,085
Average Income ($m)	0.742	0.667	0.275	0.413	0.622	0.882	1.255	4,085
Average Wealth ($m)	0.534	1.214	0.049	0.121	0.275	0.573	1.11	3,984
Income Risk (/100)	0.005	0.008	0.001	0.002	0.003	0.005	0.008	4,085
Age	57.09	13.896	40	46	56	66	78	4,085
White	0.907	0.29	1	1	1	1	1	4,085
Male	0.893	0.309	0	1	1	1	1	4,085
Education	14.597	2.229	12	12	16	16	17	4,055

Table 4: Cross-sectional Determinants of Entry and Exit into Non-Retirement Accounts – Cont'd

Panel B: Cross-Sectional Regression Estimates						
	(1) Log(1 + Entries)	(2) Log(1 + Exits)	(3) Log(1 + Entries/Exits)	(4) I(Entries>0)	(5) I(Exits>0)	(6) I(Entries/Exits>0)
Average Income ($m)	−0.013	−0.026	−0.034	−0.007	−0.043	−0.034
	(−0.91)	(−1.61)	(−1.48)	(−0.29)	(−2.39)	(−2.33)
Average Wealth ($m)	−0.041	−0.025	−0.048	−0.093	−0.013	−0.016
	(−4.56)	(−1.86)	(−2.68)	(−4.33)	(−1.13)	(−1.56)
Income Risk (/100)	2.638	1.062	2.695	9.477	1.546	5.206
	(3.72)	(1.80)	(3.46)	(4.69)	(1.43)	(3.16)
Age	−0.003	−0.002	−0.004	−0.004	−0.004	−0.005
	(−5.95)	(−3.11)	(−5.70)	(−5.91)	(−5.38)	(−8.74)
White	−0.067	−0.059	−0.087	−0.081	−0.095	−0.054
	(−2.81)	(−2.62)	(−2.83)	(−2.79)	(−3.43)	(−2.37)
Male	−0.025	−0.04	−0.051	−0.018	−0.061	−0.038
	(−0.90)	(−1.59)	(−1.49)	(−0.53)	(−1.94)	(−1.52)
Education	−0.027	−0.032	−0.046	−0.037	−0.046	−0.045
	(−8.33)	(−9.88)	(−10.82)	(−8.31)	(−10.89)	(−11.82)
Constant	1.204	1.286	1.979			
	(19.15)	(20.43)	(23.89)			
N (Observations)	3,954	3,954	3,954	3,954	3,954	3,954
R^2 [Pseudo R^2]	0.066	0.058	0.086	[0.074]	[0.074]	[0.125]

Table 5: Probability of Entry and Exit in Non-Retirement Accounts: 2007-09 SCF Panel

This table reports the marginal effects from probit regressions. The dependent variable is the decision to exit from non-retirement investment accounts (Regressions (1) to (2)) or start investing in non-retirement accounts (Regressions (3) to (4)) in year 2009. We estimate the regressions using the analytical sample weights provided by the SCF. We report, beneath the estimates, t-statistics based on standard errors corrected by the SCF analytical sample weights. Detailed variable descriptions are included in Table A.1.1 in the Appendix.

	Owners in 07 Exiting in 09		Non-Owners in 07 Entering in 09	
	(1)	(2)	(3)	(4)
White	−0.032	−0.023	0.065	0.060
	(−1.90)	(−1.59)	(2.81)	(2.59)
Male	−0.028	−0.014	0.021	−0.001
	(−1.80)	(−1.03)	(0.88)	(−0.04)
Age 07 (/100)	0.013	0.006	−0.051	−0.035
	(0.29)	(0.15)	(−0.75)	(−0.50)
Education 07	−0.015	−0.010	0.023	0.018
	(−5.37)	(−4.24)	(4.80)	(3.86)
Income 07	−0.297	−0.519	2.403	2.937
	(−3.11)	(−4.46)	(7.00)	(8.11)
Financial Wealth 07	−0.042	−0.120	0.467	0.680
	(−3.23)	(−10.96)	(3.51)	(4.90)
Risk Tolerance 07	0.046	0.037	−0.021	−0.023
	(5.45)	(5.11)	(−1.45)	(−1.60)
DIncome ($m)		−0.547		1.710
		(−4.10)		(4.17)
DRetire W ($m)		−0.032		0.697
		(−1.17)		(2.26)
DFin W ($m)		−0.122		0.329
		(−11.96)		(3.07)
DHousing W ($m)		−0.046		0.183
		(−1.70)		(2.51)
N (Observations)	2,539	2,539	1,318	1,318
Pseudo R^2	0.062	0.064	0.122	0.160

Table 6: Simulated Method of Moment (SMM) Estimates: Baseline Results

This table reports the model estimation results using the SMM. Panel A reports the estimated parameters and Panel B describes the moments of the model.

Panel A: Parameter Estimates		
Parameter		Baseline
γ		3.087
		(3.88)
β		0.970
		(5.31)
Ψ		0.988
		(4.92)
J-statistic		0.111
p-value of J test		0.010
Panel B: Moment Estimates		
Moment	Data	Baseline
Probit Est(Current Part | Past Part)	0.510	0.493
Ownership Turnover = Entry + Exit Rates	0.160	0.240
Always Participate	0.328	0.198
Average Participation in a Year	0.489	0.657
Rebalance of Equity Share	0.486	0.522
Portion of Delegators	0.642	0.735
Equity Share	0.413	0.694
Median of Fin. Wealth to Wages (Stockholders)	1.034	0.936
Median of Fin. Wealth to Wages (All Households)	0.425	0.592
α_1- 1 Quarter	0.030	0.031
α_1- 4 Quarters	0.127	0.071
α_1- 16 Quarters	0.352	0.099

Table 7: Moment Estimates and Costs to Equity Ownership and Trading

This table reports how the moments used in the SMM estimation respond to variations in the cost parameters. In Columns (1) and (2), we report the data moments and implied moments from the baseline estimation in Table 6, respectively. In Column (3) we report the moments when investing in the risky asset is costless (i.e., $FC = 0$; $C = 0$; $\Psi = 1$). In Column (4), we allow for only fixed ownership costs (i.e., $FC \neq 0$; $C = 0$; $\Psi = 1$). In Column (5), we allow for fixed ownership costs and the cost of portfolio self-management (i.e., $FC \neq 0$; $C = 0$; $\Psi \neq 0$). In Column (6), we allow for fixed ownership costs and trading costs (i.e., $FC \neq 0$; $C \neq 0$; $\Psi = 1$). In the last row, we report the mean squared error (MSE) of each simulation, which is based on the difference between the data and model-implied moments.

	(1) Data	(2) Baseline	(3)	(4)	(5)	(6)
		$FC \neq 0$	$FC = 0$	$FC \neq 0$	$FC \neq 0$	$FC \neq 0$
		$C \neq 0$	$C = 0$	$C = 0$	$C = 0$	$C \neq 0$
		$\Psi \neq 0$	$\Psi = 1$	$\Psi = 1$	$\Psi \neq 0$	$\Psi = 1$
Probit Est(Current Part | Past Part)	0.510	0.493	0.062	0.062	0.475	0.095
Ownership Turnover = Entry + Exit Rates	0.160	0.240	0.126	0.126	0.249	0.184
Always Participate	0.328	0.198	0.588	0.589	0.204	0.482
Average Participation in a Year	0.489	0.657	0.967	0.967	0.665	0.931
Rebalance of Equity Share	0.486	0.522	1.000	1.000	0.543	0.993
Equity Share	0.413	0.694	0.997	0.997	0.704	0.980
Portion of Delegators	0.642	0.735	0.000	0.000	0.727	0.000
Median of Fin Wealth to Wages (Stockholders)	1.034	0.936	0.748	0.749	0.939	0.781
Median of Fin Wealth to Wages (All Households)	0.425	0.592	0.633	0.633	0.600	0.641
α_1- 1 Quarter	0.030	0.031	0.037	0.037	0.029	0.036
α_1- 4 Quarters	0.127	0.071	0.086	0.085	0.065	0.078
α_1- 16 Quarters	0.352	0.099	0.075	0.074	0.105	0.041
MSE ($\times 100$)		14.29	37.85	37.85	14.58	36.42

Table 8: Moment Estimates with Higher Income Risk and Higher Stock-Market Risk

This table reports estimated simulated moments with an exogenous change in the risk environment faced by households. Column (1) reports the empirical moments. Column (2) reports the model moments implied by the baseline estimation from Table 6. Column (3) shows the model moments when idiosyncratic household income risk is increased by 25% compared to the baseline case. Column (4) shows the model moments when we allow for a stock market crash in the process of the risky asset. In the last row, we report the mean squared error (MSE) of each simulation, which is based on the difference between the data and model-implied moments.

	(1)	(2)	(3)	(4)
Moment	Data	Baseline	High Income Risk	Stock Market Crash
Probit Est(Current Part | Past Part)	0.510	0.493	0.426	0.524
Ownership Turnover = Entry + Exit Rates	0.160	0.240	0.291	0.240
Always Participate	0.328	0.198	0.310	0.161
Average Participation in a Year	0.489	0.657	0.709	0.589
Rebalance of Equity Share	0.486	0.522	0.605	0.423
Equity Share	0.413	0.694	0.701	0.445
Portion of Delegators	0.642	0.735	0.482	0.601
Median of Fin Wealth to Wages (Stockholders)	1.034	0.936	1.397	0.905
Median of Fin Wealth to Wages (All Households)	0.425	0.592	1.056	0.530
α_1- 1 Quarter	0.030	0.031	0.036	0.024
α_1- 4 Quarters	0.127	0.071	0.079	0.053
α_1- 16 Quarters	0.352	0.099	0.121	0.140
MSE (×100)		14.29	25.52	10.38

Appendix

A.1 Definitions of Key Empirical Variables

Table A.1.1: Variable Definitions

The table presents definitions of the variables extracted from the SCF and the PSID.

Variable	Description	Source
Stock Owner	1 if own stock in non-retirement investment accounts, 0 otherwise	PSID
Stock Owner	1 if portion of wealth allocated to non-IRA stocks>0, 0 otherwise	SCF
Past Participation	1 if owner of non-retirement accounts in the past wave, 0 otherwise	PSID/SCF
Always Participate	Fraction of households that own non-retirement accounts in all waves	PSID
Equity Share	Holdings in non-retirement accounts, divided by financial assets	SCF
Financial Wealth to Wages	Value of financial assets, divided by labor income	SCF
Trading Indicator	1 if the household buys/sells stocks in non-retirement accounts, 0 otherwise	PSID
Rebalancing Rate	Average of the trading indicator	PSID
Entry	1 if stock owner in wave t but not in $t-1$, 0 otherwise	PSID/SCF
Exit	1 if not a stock owner in wave t but owner in $t-1$, 0 otherwise	PSID/SCF
Turnover	1 if the household entry or exit dummy variable is 1, 0 otherwise	PSID/SCF
Log of (1 + Entries)	The log of 1 plus the total number of entries in non-retirement accounts between 1999 and 2011	PSID
Log of (1 + Exits)	The log of 1 plus the total number of exists from non-retirement accounts between 1999 and 2011	PSID
Log of (1 + Entries and Exits)	The log of 1 plus the number of entries and exits from non-retirement accounts between 1999 and 2011	PSID
I(Entries>0)	1 if household owns non-retirement accounts at least once, 0 otherwise	Created
I(Exits>0)	1 if household sells all assets in non-retirement accounts at least once, 0 otherwise	Created
I(Entries/Exits>0)	1 if household enters or exits non-retirement accounts at least once, 0 otherwise	Created
White	1 if the household race is White, 0 otherwise	PSID/SCF
Male	1 if the household gender is male, 0 otherwise	PSID/SCF
Age	Years old	PSID/SCF
Education	Years of schooling	PSID/SCF
Risk Aversion	Response to a categorical question on the amount of financial risk that the respondent is willing to take	SCF 07
Wage/Income	Labor earnings	PSID/SCF
Wealth	Assets − Liabilities	PSID/SCF
Income Risk	The standard deviation of the biennial income growth between 1999 and 2011	PSID
DIncome	Labor income (wages and salaries) in 2009 minus labor income 2007	SCF
DRetire W	Value of retirement assets in 2009 minus value of retirement assets in 2007	SCF
DFin W	Financial assets of 2009 minus financial assets of 2007	SCF
DHousing W	Value of housing 2009 minus value of housing 2007	SCF

A.2 Life Cycle Considerations

In this appendix, we present the statistics using a sub-sample that includes households only within the 35 to 60 year age range.

Table A.2.1: Ownership Turnover in Non-Retirement Accounts: PSID, 1999-2011 for Households Aged 35 to 60

This table reports statistics using the PSID waves from 1999 to 2011 for households between the ages of 35 to 60 only. Panel A reports various ownership in non-retirement accounts. Column (1) reports the ownership rates per wave. Column (2) reports the fraction of new owners in year $t+2$ as a fraction of all households. Column (3) reports the fraction of households that did not own non-retirement accounts in year t but became new owners in the year $t+2$ as a fraction of all households. Column (4) reports the fraction of non-owners in year t that enter non-retirement accounts in year $t+2$ as a fraction of all owners in year t. Column (4) reports the fraction of owners in year t that exit (sell their holdings in non-retirement accounts) in year $t+2$ as a fraction of all owners in year t. Panel B reports the entry and exit statistics for the baseline cohort of stockholders: owners of non-retirement accounts in the 1999 wave. Column (1) reports the fraction of this baseline cohort who participate in non-retirement accounts in any of the future waves. Column (2) reports the fraction of 1999 owners who exit non-retirement accounts in a particular wave. Column (3) reports the fraction of the baseline owners in year t who participated in non-retirement accounts in each of the previous waves. Column (4) reports the fraction of baseline owners who re-enter non-retirement accounts after having exited in a previous wave. Panel C reports the portfolio rebalancing rates for owners of non-retirement accounts. Specifically, we present the average of the trading indicator across households by year.

Panel A: Entry and Exit Statistics PSID 1999 Cohort					
	(1)	(2)	(3)	(4)	(5)
	Ownership	% of All Households$_t$		% of Stockholders$_t$	
Wave	Rate	Entry$_{t+2}$	Exit$_{t+2}$	Entry$_{t+2}$	Exit$_{t+2}$
1999	25.9%	-	-	-	-
2000	28.0%	10.9%	8.6%	32.7%	25.7%
2003	23.7%	6.7%	11.1%	18.8%	31.1%
2005	23.6%	7.8%	7.9%	25.6%	25.8%
2007	22.0%	6.8%	7.3%	23.0%	24.5%
2009	19.9%	5.2%	8.5%	18.5%	30.0%
2011	16.4%	4.9%	9.2%	20.9%	39.0%
Average	22.8%	7.1%	8.8%	23.2%	29.4%

Table A.2.1: Ownership Turnover in Non-Retirement Accounts: PSID, 1999-2011 for Households Aged 35 to 60 – Cont'd

Panel B: Tracking the Owners: 1999 Wave

Wave	(1) Ownership Rates of 1999 Owners in Future Waves	(2) Exit of 1999 Owners	(3) 1999 Owners who Own Non-Ret A/c in Previous Waves	(4) 1999 Owners who Exited and Re-entered
1999	100.0%	-	100.0%	-
2001	75.7%	24.3%	75.7%	-
2003	66.4%	9.4%	57.3%	34.0%
2005	66.5%	0.2%	50.5%	23.6%
2007	64.7%	1.8%	45.2%	20.4%
2009	54.7%	10.0%	38.5%	11.7%
2011	49.9%	4.9%	30.4%	10.0%

Panel C: Average Trading Levels

	Year							
	1999	2001	2003	2005	2007	2009	2011	Average
% Trading	-	0.581	0.484	0.529	0.477	0.437	0.462	0.495

Table A.2.2: Summary Statistics: SCF, Households Aged 35 to 60

This table reports statistics computed with data from the Survey of Consumer Finances (SCF). We use the triennial SCF waves from 1995, 1998, 2001, 2004, 2007, and 2010. We also use the SCF panel for the years 2007 and 2009. All the reported statistics are for households between the ages of 35 to 60 only. By stockholder (non-stockholder) we refer to households that have some (zero) wealth in non-retirement investment accounts. Panel A reports the statistics for entry and exit in non-retirement accounts using the SCF 2007-2009 panel. Specifically, we report the ownership statuses ("Own" and "Not Own") over the two years. Panel B reports the household participation rate in non-retirement accounts for the survey years from 1995 to 2010. Panel C reports summary statistics of wage and equity for the years 2007 and 2009. Specifically, for each sample examined, the columns report the mean and median of equity and wage in 2007 and 2009. The samples include "All households"; those who own equity in non-retirement accounts in the year 2009 ("Stockholders 09"); those who own equity in non-retirement accounts in the year 2007 ("Stockholders 07"); those who enter investing in non-retirement accounts in the year 2009 but were not investors in 2007 ("Entering Stockholders"); and finally, those who did not invest in non-retirement accounts (equity=0) in the year 2009, but invested in 2007 (equity>0), (Exiting Stockholders"). Panel D focuses on households that exit non-retirement accounts (stockholders in 2007 and not 2009) and those who enter investing in non-retirement accounts (stockholders in 2009 but not 2007). The column labeled "Averages" reports the average stockholdings for exiting or entering households. The column labeled "% of 09 equity" reports the average stockholding as a percentage of average equity held by all stockholders in 2009. The column labeled "% of average 09 earnings" reports average stockholdings as a percentage of average labor earnings of stockholders in 2009. Panel E reports ratios of stock holdings in non-retirement accounts, wealth, and wage, where the top row labeled "Survey year" reports the survey year. Panel E.1 reports statistics for households with wealth in non-retirement accounts, where the first row labeled "Equity share" reports the median stock holdings divided by financial wealth. The second row labeled "Median of Fin. Wealth to Wages (Stockholders)" reports the median of financial wealth divided by wage. Panel E.2 reports statistics for all households (stockholder and non-stockholder), where the first row labeled "Median of Fin. Wealth to Wages (All Households)" reports the median wealth to wage ratio for all households.

Panel A: Entry and Exit - 2007-09 SCF Wave

Year/Year:	2009	
2007	Not Own	Own
Not Own	45.4%	6.4%
Own	9.7%	38.5%

Panel B: Participation Rates - 1995 to 2010 Triennial SCF Waves

	Year						
	1995	1998	2001	2004	2007	2010	Average
Part Rate	0.470	0.582	0.605	0.571	0.605	0.552	0.564

Table A.2.2: Summary Statistics: SCF, Households Aged 35 to 60 – Cont'd

Panel C: Wage and Equity in Non-Retirement Accounts - 2007-09 SCF Panel										
	All Households		Stockholders 09		Stockholders 07		Entering Stockholders		Exiting Stockholders	
Statistics	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
2007 Equity	\$122,266	5,903	189,805	36,246	202,550	1,147,599	-	-	42,822	10,356
2007 Wage	\$74,925	53,249	99,450	71,353	102,893	192,579	49,832	42,599	62,112	47,924
2009 Equity	\$97,288	6,500	154,384	35,000	157,297	759,616	26,407	6,300	-	-
2009 Wage	\$72,878	50,806	97,881	73,719	99,410	153,375	54,421	44,829	50,707	37,856
Panel D: Exit and Entry Volume in Non-Retirement Accounts - 2007-09 SCF Panel										
Status	Average Ownership		% of Average 2009 Equity		% of Average 2009 Earnings					
Exit	\$42,822		27.7%		43.8%					
Entry	\$26,407		17.1%		27.0%					
Panel E: Financial Wealth and Wage - SCF Triennial Waves										
	Survey Year									
	1989	1992	1995	1998	2001	2004	2007	2010		Average
Panel E.1: Wealth Shares for Household with Non-Retirement Accounts (i.e., Stockholders)										
Stock/Fin	0.28	0.35	0.44	0.49	0.52	0.49	0.48	0.42		0.43
Fin/Wage	0.78	0.95	0.95	1.17	1.29	1.28	1.32	1.19		1.12
Panel E.2: Median Financial Assets by Wage, All Households										
Fin/Wage	0.41	0.39	0.44	0.67	0.72	0.59	0.73	0.47		0.55

Table A.2.3: Household-Level Moment Estimates for SMM: All Ages and Aged 35 to 60

This table reports the household-level moments we use for our SMM estimation results of the model by SMM. Column (1) labeled "Moment" reports the name of the moments. Column (2) labeled "Full Sample" reports moment values calculated from the full sample. Column (3) labeled "35 - 60 Sample" reports moment values calculated from the data using only households within the age range of 35 to 60.

Moment	Full Sample	35 - 60 Sample
Probit Est(Current Part | Past Part)	0.512	0.521
Ownership Turnover = Entry + Exit Rates	0.160	0.158
Always Participate	0.328	0.304
Participated in First and Last Year	0.508	0.499
Average Participation in a Year	0.492	0.564
Rebalance of Equity Share	0.486	0.495
Equity Share	0.413	0.434
Median of Fin Wealth to Wages (Stockholders)	1.034	1.118
Median of Fin Wealth to Wages (All Households)	0.425	0.553

A.3 Estimation of Household Income Process

We estimate the income process (11) with annual data from the PSID. Our sample period is 1967-1993. We use data until 1993 since the PSID has annual surveys until 1993. After that, the surveys are administered every two years. In the estimation, we deflate the labor income levels using the CPI obtained from the Bureau of Labor Statistics. We estimate the income process with a restricted sample where the household head is: (i) male,[23] (ii) between 20 to 64 years old, and (iii) not from the SEO sample. We also require that the real hourly labor earnings of the household head are between \$2 and \$400. Finally, we focus on households where the head of household works between 520 hours (10 hours per week) and less than 5,110 hours (14 hours a day, every day).

We estimate the income process with the two-step approach of Bonaparte, Cooper, and Zhu (2012). We first pool the observations across all individuals and regress income on demographics, such as age, age squared, and education attainment. We treat the explained part of this regression as the deterministic component of income. We use the error term from the demographic-based regression to capture the unobservable stochastic component of income. We assume that the stochastic component of income follows an AR(1) process. We fit the AR(1) process to the residuals and find that the autocorrelation parameter ρ is 0.842. Finally, using the estimation of the AR(1) process, we obtain the standard deviation of the innovation ϵ, which is 0.290.

Given that in the SMM estimation is that the quarterly frequency, we translate the estimated annual income process into the quarterly frequency using the methodology of (Tauchen and Hussey 1991). Then, we transform the quarterly income process into a five-state Markov chain following Tauchen (1986). We impute the Markov chain into our model and its estimation. Also, in the Markov chain, we set the average level of real income to \$18,000 to mimic the average level of real income in our PSID sample, which is \$72,000.

[23] We focus on males following the income profile literature. For instance, see Guvenen (2007).

A.4 Estimation of Proportional Trading Cost Function

In this section, we provide the estimates of the proportional trading cost function. The estimation follows Bonaparte, Cooper, and Zhu (2012). As in Bonaparte, Cooper, and Zhu (2012), we assume that overall trading costs are a quadratic function of the trade value v.

Table A.4.1: Estimation of Proportional Trading Costs Function

This table reports regression results for the cost of trading (buying and selling stock), where the dependent variable is the commission, and the independent variables are trade value (the price of the share times the quantity of share) and trade value squared. If a stockholder buys different stocks in a given month, the stockholder reports the commission, quantity, and price on each one of these stocks separately. The data is from the Barber and Odean (2000) study that contains information on common stock trades of about 78,000 stockholders who are clients of a discount brokerage firm from January 1991 to December 1996. The numbers in parentheses are t-statistics, which are based on standard errors clustered at the account level.

Parameter	Buying	Selling
Constant v_0^i	56.106	61.437
	(64.32)	(129.05)
Linear v_1^i	0.001	0.001
	(14.69)	(36.72)
Quadratic v_2^i	$-2.88E$-13	$-9.26E$-13
	(-5.78)	(-2.43)
N Obs.	1,746,403	1,329,394
R^2	0.251	0.359

A.5 Model Computation

We implement the simulated method of moments estimation by solving the model with a value function iteration approach. The model frequency is quarterly, which allows to compute moments with the simulated data at the quarterly, annual, and bi-annual frequency. This is important because the data moments we match are at frequencies ranging from quarterly to bi-annual. Below, we provide the details of this methodology.

The state-space of the dynamic optimization problem is determined by y, s_{-1}, b_{-1}, and R_{-1}. y is income of the current period; s_{-1} and b_{-1} are the beginning-of-period asset holdings of risky stocks with return R_{-1} and riskless bonds with return r, respectively. In solving the model, we make the following assumption about the income and return processes. First, as mentioned in Appendix A.3, we transform the estimated income process to a five-state Markov chain following the Tauchen (1986) method. Second, we assume that the stock return process is an IID process with three return states. Its quarterly standard deviation of 8.3%. For simplicity, we require the stock return and the income process to be uncorrelated. Third, we fix the return of the risk-free asset to be 1% per annum (or $1.0\%/4 = 0.25\%$ on a quarterly basis).

In the model, at the beginning of each period, a stockholder makes the decision regarding how much of his wealth and income to consume and how much to allocate to stocks and bonds. This is a high-dimensional programming problem and it is computationally intensive. To solve the model with good precision within a reasonable amount of time, we implement the following strategy to solve for the decisions of a stockholder:

1. We assume that the choice of stock holdings (control variable) is made before the realization of the return of the risky asset. Thus, in our model simulation, we first solve for the control variable of stock holdings and then multiply it with the return to make it a state variable for the next period.

2. We utilize a mixture of grid search and spline interpolation to execute the value function

iteration. In particular, we define a coarse grid with 25 points for stock holdings and 20 points for bond holdings, denoted $s_{coarse} \times b_{coarse}$. Then, we turn to a fine grid with 400 by 150 grid points, denoted as $s_{fine} \times b_{fine}$.

Finally, to operationalize the value-function iteration, we guess the value function values for each discrete state variable, and then update the value function as follows:

1. We compute the value of the sub-optimal decision of not adjusting stock holdings, denoted by $v^n = (D, s_{coarse} \times b_{coarse})$, where D is the product of discrete state variables on the coarse grid. The value of the sub-optimal decision of always adjusting stock holdings, denoted by $v^\alpha = (D, s_{coarse} \times b_{coarse})$, is also computed.

2. We then use the values of $v^n = (D, s_{coarse} \times b_{coarse})$ and $v^\alpha = (D, s_{coarse} \times b_{coarse})$ to interpolate the values on the fine grid, denoted by $v^n = (D, s_{fine} \times b_{fine})$ and $v^\alpha = (D, s_{coarse} \times b_{coarse})$. For the interpolation, we use spline interpolation since the value function is highly non-linear.

3. Finally, we compute the updated value function as:

$$v(D, s_{fine} \times b_{fine}) = max\{v^n(D, s_{fine} \times b_{fine}), v^\alpha(D, s_{fine} \times b_{fine})\}.$$

The policy function and the simulated data are computed on the fine grid after the convergence of the value function. The coarse grid and fine grid are designed cautiously since high upper bounds reduce the efficiency of the optimization routine, while low upper bounds cause stockholders optimal decision rules to be distorted. To address these issues, and based on several experiments, we place more points near the lower-bounds of the asset holdings grid. Specifically, the optimal upper-bound for stock holdings is 40 times the mean income and 20 times the mean income for bond holdings. We impose a lower bound on assets to be zero, so there is no shorting. Finally, we draw random shocks to income and returns for 500 stockholders for 800 periods (quarters), which implies the dimension of simulated data is 500×800.