

Risk Aversion and Wealth: Evidence from Person-to-Person Lending Portfolios*

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Abstract

We estimate risk aversion from investors' portfolio choices on a person-to-person lending platform. Our method obtains a risk aversion parameter from each investment and generates a panel that we use to disentangle the elasticity of risk aversion to wealth from heterogeneity in risk attitudes across investors and changes in beliefs. We find an average income-based Relative Risk Aversion of 2.85, a median of 1.62, and substantial heterogeneity and skewness across investors. Risk aversion increases after a negative housing wealth shock, consistent with Decreasing Relative Risk Aversion. We show that ignoring heterogeneity and changes in beliefs would lead to biased estimates.

JEL codes: E21, G11, D12, D14.

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1 Introduction

Theoretical predictions on investor behavior and asset prices, investment and the cost of business cycle depend crucially on assumptions about the relationship between risk aversion and wealth.¹ Although characterizing this relationship has long been in the research agenda of empirical finance and economics, progress has been hindered by the difficulty of disentangling the change in risk aversion due to wealth shocks from the effect of heterogeneity in risk attitudes across agents and changes in beliefs over time and across investors. In this paper we estimate risk aversion parameters from investors' actual financial decisions on Lending Club, a leading U.S. based person-to-person lending platform where individuals can invest in diversified portfolios of small loans. We develop a methodology that measures risk aversion from each portfolio choice, and since we observe the same individuals make multiple investment decisions, we build a panel of risk aversion parameters and use it to estimate the elasticity of risk aversion to wealth. In addition, the features and rules of this market allow us to control for the effect of investor beliefs and their evolution over time.

Our paper belongs to a growing literature that uses peer-to-peer lending platforms as a laboratory to study various economic and financial decisions. This market has now generated more than 1.5 billion dollars in loans in the US, and its model has spread across the world. Among others, Iyer et al. (2011) use this setting to analyze lenders' ability to infer borrowers' creditworthiness in an unintermediated market, while Lin et al. (2012) examine social networks and adverse selection. Its advantage is that the researcher has an unusual amount of detailed information about the environment and the investors' choices and at the same time that the subjects analyzed are real investors making actual financial decisions. The paper is also related to the literature on risk aversion based on micro-evidence on individual financial choices (Guiso et al., 2011; Barseghyan et al., 2013; Cohen and Einav, 2007), and to the household finance literature on individual investment and borrowing decisions (Seru et al., 2010).

Due to data limitations, the bulk of existing work is based on comparisons of risk aversion across investors of different wealth observed at the same point in time. In such settings inferring how an

¹See Kocherlakota (1996) for a discussion of the literature on the equity premium and the risk free rate puzzles under different preference assumptions.

investor's risk aversion would change after a wealth shock requires very restrictive assumptions (Chiappori and Paiella, 2011). If risk attitudes are heterogeneous in the population, a negative relationship between risk aversion and wealth in the cross section contains no information indicating that an individual's risk aversion would drop if his wealth increased. Such negative relationship could be due to individuals with different risk attitudes ending up with different wealth levels, for example because of the different types of investments they make, even if each individual's risk aversion was constant in response to changes in wealth, or even increasing in wealth.²

Important recent work improves on the cross-sectional approach by looking at panel data and changes in the fraction of risky assets in an investor's portfolio stemming from the time series variation in investor wealth.³ The crucial identifying assumption required for using the share of risky assets as a proxy for investor Relative Risk Aversion (RRA) in this setting, is that all other determinants of the share of risky assets remain constant as the investor's wealth changes. One must assume, for example, that changes in financial wealth resulting from the performance of risky assets are uncorrelated with changes in the investor's beliefs about their expected return and risk. Attempts to address this identification problem through an instrumental variable approach have produced mixed results: the estimated sign of the elasticity of RRA to wealth varies across studies depending on the choice of instrument.⁴ Finally, estimates of risk aversion based on the share of risky assets, both in the cross section and with panel data, pose an additional problem when used to analyze the link between risk preferences and wealth: Measurement error in wealth is inherited by the risk aversion estimates, and may induce a spurious correlation between the two. This potentially explains why existing empirical evidence on the correlation between risk preferences and wealth is inconclusive, depends on the definition of wealth, and is sensitive to the categorization of assets into the risky and riskless categories.⁵

In this paper we take a different approach and develop a methodology to estimate the local curvature of an investor's utility function (Absolute Risk Aversion, or ARA) from each portfolio

²Guvenen (2009) and Gomes and Michaelides (2008) propose a model with preference heterogeneity that endogenously generates cross sectional variation in wealth. Alternatively, an unobserved investor characteristic, such as having more educated parents, may jointly affect wealth and the propensity to take risk.

³Chiappori and Paiella (2011), Brunnermeier and Nagel (2008) and Calvet et al. (2009).

⁴See Calvet et al. (2009) and Calvet and Sodini (2009) for a discussion.

⁵See, among others, Morin and Suarez (1983), Blume and Friend (1975), and Cohn et al. (1975).

choice, based on idiosyncratic risk and independent from the measurement of outside wealth. Our estimation method is derived from an optimal portfolio model in which investors hold not only the market portfolio, but also securities for which they have subjective insights (Treyner and Black, 1973). We apply this methodology to the analysis of the risk taking behavior of 2,168 individuals investing in diversified portfolios of small loans on Lending Club (LC). Investments in LC are treated as part of a potentially bigger set of special-insight securities, i.e. securities that the investors believe to have an excess return due to their insights. We then decompose the LC returns into a systematic component, correlated with other securities through a common factor (Sharpe Diagonal Model), and an additional return component orthogonal to the market. We use the latter component to characterize investors' preferences. An investor's ARA is given by the additional expected return that makes her indifferent about allocating the marginal dollar to a loan with higher idiosyncratic default probability. Estimating risk preferences from the non-systematic component of returns implies that the estimates are independent from the investors' overall risk exposure or wealth. In estimating risk attitudes based on idiosyncratic risk our approach is similar to that of the economic literature that studies insurance choices (Cohen and Einav, 2007; Barseghyan et al., 2013; Einav et al., 2012).⁶ In addition, by measuring the curvature of the utility function directly from the first order condition of this portfolio choice problem, we do not need to impose a specific type of utility function. While for simplicity in the remainder of the paper we illustrate our methodology using expected utility, in the Appendix we show that our method generates consistent estimates for the curvature of the utility function under alternative preference specifications, such as loss aversion and narrow framing (Barberis and Huang, 2001; Barberis et al., 2006). This is a key feature of our estimation procedure since the expected utility framework on overall wealth has been criticized as a model of agents' behavior because it cannot reconcile the observed high levels of risk aversion in small stake environments with the observable behavior of agents in environments with larger stakes (Rabin, 2000).

The average ARA implied by the tradeoff between expected return and idiosyncratic risk in our

⁶Other real life environments based on idiosyncratic risk that have been analyzed in the literature are racetrack betting (Jullien and Salanie, 2000; Chiappori et al., 2008; Chiappori et al., 2009) and TV shows (Bombardini and Trebbi, 2013 and Post et al., 2008).

sample of portfolio choices is 0.037. Our estimates imply an average income-based Relative Risk Aversion (income-based RRA) of 2.85, with substantial unexplained heterogeneity and skewness.⁷ Experimental measures of risk aversion are a good first benchmark for our estimates because investors in our model face choices similar to those faced by experimental subjects along important dimensions. Our model transforms a complex portfolio choice problem into a choice between well defined lotteries of pure idiosyncratic risk, where returns are characterized by a discrete failure probability (i.e., default), and the stakes are small relative to total wealth (the median investment in LC is \$375). The level, distribution, and skewness of the estimated risk aversion parameters are similar to those obtained in a variety of settings including the laboratory, surveys and field experiments.⁸ These similarities indicate that investors in our sample, despite being a self-selected sample of individuals who invest on-line, have risk preferences similar to individuals in other settings.

We then estimate the elasticity of risk aversion to changes in wealth exploiting the panel nature of the data. As a wealth shock, we use the decline in house prices in the investor’s zip code during our sample period—October 2007 to April 2008. The results indicate that the average investor’s RRA increases after experiencing a negative housing wealth shock, with an estimated elasticity of -1.82.⁹ This is consistent with investors exhibiting Decreasing Relative Risk Aversion, and with theories of habit formation (as in Campbell and Cochrane, 1999) and incomplete markets (as in Guvenen, 2009).¹⁰

In addition to the ARA inferred from the idiosyncratic component of the portfolio, our estimation method also allows to measure investors’ assessments about the systematic risk of LC loans and its evolution over the time. We find that on average, the LC systematic risk premium increases from 6.3% to 9.2% between the first and last three months of the sample, indicating that investors’ priors on LC’s systematic risk increase substantially during the period. Our finding that investors’ priors on LC systematic risk increase after house prices decline also indicates that wealth shocks

⁷The income-based RRA is a risk preference parameter often reported in the experimental literature. It is obtained assuming that the investor’s outside wealth is zero; that is: Income-based $RRA = ARA \cdot E[y]$, where $E[y]$ is the expected income from the lottery offered in the experiment.

⁸See for example Barsky et al. (1997), Holt and Laury (2002), Choi et al. (2007), and Harrison et al. (2007).

⁹The wealth-based RRA is not directly observable, we compute its elasticity from the following relationship: $\xi_{RRA,W} = \xi_{ARA,W} + 1$, where $\xi_{RRA,W}$ and $\xi_{ARA,W}$ refer to the wealth elasticities of RRA and ARA, respectively.

¹⁰These preference specifications are also consistent with the empirical findings in Calvet et al. (2009). Brunnermeier and Nagel (2008), on the other hand, find support for CRRA.

are potentially correlated with general changes in investors' beliefs. This implies that the share of risky assets may not be a valid measure of investor RRA in the presence of wealth shocks, as it might change simply because of changes in investor beliefs about future risk and returns. In our context, for example, inference based on the share of risky assets alone would have overestimated the elasticity of risk aversion to wealth.

We also compare the panel results with the cross sectional evidence from our sample. Using imputed net worth as a proxy for wealth in the cross section of investors, we find that wealthier investors exhibit lower ARA and higher RRA when choosing LC loan portfolios.¹¹ Our preferred specification, which corrects for measurement error in the wealth proxy using house prices in the investor's zip code as an instrument, obtains an elasticity of ARA to wealth of -0.059, which implies a cross sectional wealth elasticity of the RRA of 0.94.¹² The contrasting signs of the cross sectional and investor-specific wealth elasticities indicate that inference on the elasticity of risk aversion to wealth from cross sectional data will be biased, since risk taking behavior in the cross section of investors depends not only on the shape of the utility function but also on the joint distribution of preferences and wealth.¹³

Our empirical strategy requires two very specific assumptions. We now validate them empirically. First, the hypothesis that LC loans are part of the investors' active portfolio of special-insight securities is confirmed by the substantial heterogeneity of mean and variance across investors' portfolios. In the alternative hypothesis that loans in LC are part of the market portfolio all investors would choose portfolios of similar characteristics, which is strongly rejected by the data. Second, the features of the LC environment allow us to test for the assumption that investors' beliefs about the stochastic distribution of returns are consistent with the information provided on the LC's web site. An investor in LC can choose her investment portfolio manually or through an optimization

¹¹Net worth is imputed by Acxiom as of October 2007, the start date of our sample. Acxiom is a third party specialized in recovering consumer demographics based on public data.

¹²These findings coincide qualitatively with Guiso and Paiella (2008) and Cicchetti and Dubin (1994) who also base their analysis on risk aversion parameters estimated independently of their wealth measure.

¹³Chiappori and Paiella (2011) find the bias from the cross sectional estimation to be economically insignificant. In their case, however, changes in agent's wealth are not exogenous, and risk aversion is measured through the share of risky assets. Tanaka et al. (2010) use rainfall across villages in Vietnam as an instrument for wealth and find significant difference between the OLS and IV estimators. However, to obtain the elasticity of the agent-specific risk aversion, they must assume that preferences are otherwise equal across villages.

tool. When the choice is manual, she selects loans by processing the information on the loans' expected returns and idiosyncratic default rates herself. When she uses the tool, the tool processes this information for her, based on the default probabilities posted on the LC website, and provides all the possible efficient (minimum variance) portfolios that can be constructed with the available loans. The investor then chooses among the efficient portfolios according to her own risk preferences. Importantly, our estimation procedure and the tool use the same information on risk and return, and the same modeling assumptions regarding a common systematic component across all potential loans. Therefore, any bias arising because of the misspecification of investors' beliefs and their evolution over time would result in a wedge between the risk aversion estimates based on manual and automatic choices. We reject empirically that such a wedge exists.

Finally, we verify the consistency of investors' risk preferences across different decisions within LC, namely, the total amount to invest in LC, the loans to include in the portfolio, and the portfolio allocation across these loans. We find that the investor-specific ARA, estimated solely from the share of investment allocated to loans in the portfolio, is consistent with the investor's choice of loans to exclude from her portfolio and with the overall amount invested on the lending platform. Moreover, the estimated elasticity of risk aversion to wealth is consistent with the observed relationship between the total investment amount in LC and wealth, both in the cross section of investors and, for a given investor, in the time series. Since the ARA and elasticity estimates do not use information on foregone loans or the total investment in LC, these consistency tests constitute an independent validation of our conclusions on investors' risk taking behavior.

The rest of the paper is organized as follows. Section 2 describes the Lending Club platform. Section 3 illustrates the portfolio choice model and our estimation strategy. Section 4 describes the data and the sample. Section 5 discusses the empirical results and provides a test of the identification assumptions. Section 6 explores the relationship between risk aversion and wealth. Section 7 tests the consistency of the investor preferences across different decisions within LC. And Section 8 concludes.

2 The Lending Platform

Lending Club (LC) is an online U.S. lending platform that allows individuals to invest in portfolios of small loans. The platform started operating in June 2007. As of today, it has funded \$1.184 billion in loans and provided an average net annualized return of 8.63% to investors.¹⁴ Below, we provide an overview of the way the platform worked at the time of the study and derive the expected return and variance of investors' portfolio choices.

2.1 Overview

Borrowers need a U.S. SSN and a FICO score of 640 or higher in order to apply. They can request a sum ranging from \$1,000 to \$25,000, usually to consolidate credit card debt, finance a small business, or fund educational expenses, home improvements, or the purchase of a car.

Each application is verified by LC in terms of credit bureau information and employment and then classified into one of 35 risk buckets based on the FICO score, the requested loan amount, the number of recent credit inquiries, the length of the credit history, the total and currently open credit accounts, and the revolving credit utilization, according to a pre-specified published rule posted on the website.¹⁵ On average about 12% of the applications pass the initial screening and are classified into buckets and posted on the website. LC also posts a default rate for each risk bucket, taken from a long-term validation study by TransUnion, based on U.S. unsecured consumer loans. All the loans classified in a given bucket offer the same interest rate, assigned by LC based on an internal rule.

A loan application is posted on the website for a maximum of 14 days. After that, if it has not attracted enough investors to get fully funded, during the period analyzed in the paper, LC provided the remaining funds. All the loans have a 3 year term with fixed interest rates and equal monthly installments, and can be prepaid with no penalty for the borrower. When the loan is granted, the borrower pays a one-time fee to LC ranging from 1.25% to 3.75%, depending on the credit bucket. LC loans are unsecured and reported to the credit bureau, so that late payments,

¹⁴For the latest figures please refer to: <https://www.lendingclub.com/info/statistics.action>.

¹⁵Please refer to <https://www.lendingclub.com/info/how-we-set-interest-rates.action> for the details of the classification rule and for an example.

delinquency and default affect the borrower’s credit score. When a loan repayment is more than 15 days late, the borrower is charged a late fee that is passed to investors. Loans with repayments more than 120 days late are considered in default, and LC begins the collection procedure. If collection is successful, investors receive the amount repaid minus a collection fee that varies depending on the age of the loan and the circumstances of the collection. Borrower descriptive statistics are shown in Table 1, panel (a).

Investors in LC allocate funds to open loan applications. The minimum investment in a loan is \$25. According to a survey of 1,103 LC investors in March 2009, diversification and high returns relative to alternative investment opportunities are the main motivations for investing in LC.¹⁶ As the first screen for the investors, LC provides an optimization tool that helps them diversify and, given the amount invested, constructs the set of efficient loan portfolios that minimize the idiosyncratic variance for each level of return.¹⁷ As Figure 1, Panel (a) shows the investors can move the mouse along a slider and see the efficient portfolio for each risk-return tradeoff.¹⁸ They can then select the preferred one according to their own risk preferences. In other words, the tool helps investors to process the information on interest rates and default probabilities posted on the website into measures of expected return and idiosyncratic variance, that may otherwise be difficult to compute for an average investor. The second screen, reported in Figure 1 Panel (b), shows the investors the detailed loan composition of the portfolio they have chosen. At this point the investors can change the amount allocated to each loan, drop some loans altogether, or add others. Alternatively, they can also start from scratch and select the loans in their portfolio manually without the help of the optimization tool. Of all portfolio allocations between LC’s inception and

¹⁶To the question “What would you say was the main reason why you joined Lending Club”, 20% of respondents replied “to diversify my investments”, 54% replied “to earn a better return than (...)”, 16% replied “to learn more about peer lending”, and 5% replied “to help others”. In addition, 62% of respondents also chose diversification and higher returns as their secondary reason for joining Lending Club.

¹⁷During the period analyzed in this paper, the portfolio tool in Figure 1 appeared as the first page to the investors. LC has recently changed its interface and, before the portfolio tool page, it has added a stage where the lender can simply pick between 3 representative portfolios of different risk and return.

¹⁸If the tool has to choose between two loans belonging to the same risk bucket, and thus with the same idiosyncratic risk and return, it picks the one with the highest fraction of the requested amount that is already funded. Also, the risk measure is the variance of the diversified portfolio divided by the variance of a single investment in the riskiest loan available. As a result it is normalized between 0 and 1. Thus, while the tool provides an intuitive sorting of efficient portfolios in terms of their idiosyncratic risk, investors always need to analyze the recommended portfolios of loans to understand the actual risk level imbedded in the suggestion.

June 2009, 39.6% was suggested by the optimization tool, 47.1% was initially suggested by the tool and then altered by the investor, and the remaining 13.3% was chosen manually.¹⁹

2.2 Return and Variance of the Risk Buckets

This subsection derives the expected return and variance of the individual loans in each risk bucket, following the same assumptions as the LC platform. All the loans in a given bucket $z = 1, \dots, 35$ are characterized by the same scheduled monthly payment per dollar borrowed, P_z , over the 3 years (36 monthly installments). The per dollar scheduled payment P_z and the bucket specific default rate π_z fully characterize the expected return and variance of the investment in a loan, μ_z and σ_z^2 . In other words, according to LC's assumptions, which we follow in developing our framework below, all the loans in a given bucket are the same in terms of expected return and variance. Since this is an important assumption, we dedicate subsection 5.2 to empirically examine whether investors' unobservable and possibly heterogeneous beliefs differ from LC's assumptions in ways that invalidate our empirical strategy. We find that, despite investors' beliefs about μ_z and σ_z^2 might be heterogeneous, differ from LC's, and they do change over time, they do so in ways that are not at odds with our identifying assumptions. Therefore, in this and the following section we develop our framework making the simplifying assumptions that μ_z and σ_z^2 are the same across investors.

LC considers a geometric distribution for the idiosyncratic monthly survival probability of the individual loans: The probability that the loan survives until month $\tau \in [1, 36]$ is $\Pr(T = \tau) = \pi_z (1 - \pi_z)^\tau$.²⁰ Thus, for any loan in bucket z , the expectation and variance of the present value of the payments, P_z are:

$$\begin{aligned}\mu_z &= P_z \left[1 - \left(\frac{1 - \pi_z}{1 + r} \right)^{36} \right] \frac{1 - \pi_z}{r + \pi_z} \\ \sigma_z^2 &= \sum_{t=1}^{35} \pi_z (1 - \pi_z)^t \left(\sum_{\tau=1}^t \frac{P_z}{(1 + r)^\tau} \right)^2 + \left(\sum_{\tau=1}^{36} \frac{P_z}{(1 + r)^\tau} \right)^2 (1 - \pi_z)^{36} - \mu_z^2\end{aligned}$$

¹⁹We exploit this variation in Subsection 5.2 to validate the identification assumptions.

²⁰Although LC does not explicitly state in the web page that the probabilities of default are idiosyncratic, the optimization tool used to calculate the set of minimum variance portfolios works under this assumption.

where r is the risk-free interest rate.

For a given investor i , the idiosyncratic risk associated with bucket z decreases with the level of diversification within the bucket; that is, the number of loans from bucket z in his portfolio, n_z^i .

The resulting idiosyncratic variance is therefore investor specific:

$$\text{var} [r_z^i] = \frac{\sigma_z^2}{n_z^i}. \quad (1)$$

where r_z^i is the idiosyncratic component of the bucket's return, R_z^i .

Then, the total variance of the return on investor i 's investment in bucket z can be decomposed as follows:

$$\text{var} [R_z^i] = V_z + \frac{\sigma_z^2}{n_z^i}$$

where V_z corresponds to the bucket's non-diversifiable risk and σ_z^2/n_z^i is its idiosyncratic component.

On the contrary, the expected return of an investment in bucket z is not affected by the number of loans in the investor's portfolio; it is equal to the expected return on any loan in bucket z , μ_z , and, based on our assumptions above, it is constant across investors:

$$E [R_z] = E [R_z^i] = \mu_z. \quad (2)$$

3 Estimation Procedure

To capture the fact that most individuals invest not only in the market and the risk free asset, but also in individual securities, we use a framework adapted from Treynor and Black (1973). This model considers investors that, instead of simply holding a replica of the market portfolio, also hold securities based on their own subjective *insights* that they will generate an excess return (alpha). Person-to-person lending markets, including LC, are not well known investment vehicles among the general public. The decision to invest in LC depends on investors' knowledge of its existence and their subjective expectation that LC is, indeed, a good investment opportunity. Thus, it is reasonable to assume that investors in LC have special insights, which explains why, as we show

later, their portfolio departs from just replicating the market.

Our framework starts by recognizing that there is a high degree of comovement between securities, and specifically to our case, the probability of default of the loans in LC is potentially correlated with macroeconomic fluctuations. We use the Sharpe Diagonal Model to capture this feature and assume that returns are related only through a common systematic factor (i.e., market or macroeconomic fluctuations). Under this assumption, returns on LC loans can be decomposed into a common systematic factor and a component orthogonal to the market (we also refer to it as *independent* component).

The advantage of this model is that the optimal portfolio of LC loans depends only on the expected return and variance of the independent component, as the next subsection shows. In other words, the optimal amount invested in each LC bucket does not depend on the return covariance with the investor’s overall risk exposure, nor does it require knowing the amount and characteristics of her outside wealth.

We test the assumptions on investors’ beliefs, i.e. that they act as if there is a common systematic factor, and that LC loans are part of the active portfolio of special-insight securities in Section 5. The data strongly support both hypotheses.

3.1 The Model

Each investor i chooses the share of wealth to be invested in the $Z+2$ available securities: a security m that represents the market portfolio, with return R_m ; a security f , with risk-free return equal to 1; and Z securities with return R_z that are part of the active portfolio and in which the investor expects to receive an excess return.

We consider investments in LC as part of the active portfolio. To allow for the existence of other active investments, we let $Z \geq 35$ and denote $z = 1, \dots, 35$ the 35 risk buckets in LC. The resulting portfolio of investor i is

$$c^i = W^i \left[x_f^i + x_m^i R_m + \sum_{z=1}^Z x_z^i R_z^i \right] \quad (3)$$

where c^i stands for the investor's consumption and x_f, x_m , and $\{x_z\}_{z=1}^Z$ correspond to the share of wealth, W^i , invested in the risk-free asset, the market portfolio, and the securities in the active portfolio, respectively.

A projection of the return of each active security $z = 1, \dots, Z$ against the market gives two factors. The first is the systematic return of the security, and the second its independent return:

$$R_z^i = \beta_z^i \cdot R_m + r_z^i \quad (4)$$

We assume all risk buckets have the same systematic risk, and allow the prior about such systematic component, β_L^i , to be investor specific. That is, for all $z = 1, \dots, 35$: $\beta_z^i = \beta_L^i$. We test and validate empirically this assumption in Subsection 5.2.²¹

We can rewrite the investor's budget constraint in the following way:

$$c^i = W^i \left[x_f^i + x_{Z+1}^i R_m + \sum_{z=1}^Z x_z^i r_z^i \right] \quad (5)$$

where x_{Z+1}^i is the total exposure to market risk, given both by the investor's direct holdings of market portfolio, x_m^i , and, indirectly, by her accumulation of market risk as a by-product of the position in the active portfolio:

$$x_{Z+1}^i = x_m^i + \sum_{z=1}^Z x_z^i \beta_z^i \quad (6)$$

The assumption that all risk buckets have the same systematic risk, is equivalent to the Sharpe Diagonal Model which assumes that the returns on the LC loans are related to other securities and investment opportunities only through their relationships with a common underlying factor, and thus the independent returns, defined in equation (4), are uncorrelated.

Assumption 1. *Sharpe Diagonal Model*²²

$$\text{for all } n \neq h : \text{cov} [r_n^i, r_h^i] = 0$$

²¹Note that under this assumption, the prior about the systematic risk V_z introduced in Subsection 2.2 is investor specific and it is given by $V_z^i = (\beta_L^i)^2 \cdot \text{var} [R_m]$, for all $z = 1, \dots, 35$.

²²Allowing a time dimension, the independent returns are also uncorrelated across time.

An example of an underlying common factor is an increase in macroeconomic risk (i.e., financial crisis) triggering correlated defaults across buckets. In our setting, such a common factor is reflected in the systematic component of equation (4) and can vary across investors and over time.

The following problem describes the portfolio choice of investor i :

$$\max_{x_f, \{x\}_{z=1}^{Z+1}} Eu \left(W^i \left[x_f^i + x_{Z+1}^i R_m + \sum_{z=1}^Z x_z^i r_z^i \right] \right)$$

subject to the investor being constrained to non-negative positions in all the LC buckets and a minimum of \$25 in each bucket with a positive investment, i.e., $x_z \in 0 \cup [25, \infty)$ for $z = 1, \dots, 35$.²³

For all buckets with $x_z \geq 25$, the first order condition characterizing the optimal portfolio share is:

$$foc(x_z^i) : E[u'(c^i) \cdot W^i(r_z^i - 1)] = 0 \quad (7)$$

A first-order linearization of the first order condition (7) around expected consumption results in the following optimality condition:

$$E[r_z^i] - 1 = \left(-\frac{u''(E[c^i])}{u'(E[c^i])} \right) \cdot W^i x_z^i \cdot var[r_z^i]. \quad (8)$$

Due to the \$25 minimum investment per loan constraint, this first order condition characterizes the optimal portfolio shares in those risk buckets where there is an interior solution, e.g. where the investor chooses a positive and finite investment amount. In other words, this optimality condition describes the investment share that makes the investor indifferent about allocating an additional dollar to a loan in bucket z when investment in the bucket is greater than zero. In contrast, in corner solutions where the additional expected return is always smaller (larger) than the marginal increase in risk for any investment amount larger than \$25, investment in that bucket will be zero (infinity). We describe in detail the optimality condition that characterizes interior and corner solutions in the on-line appendix B.

²³On-line appendix B shows that the optimality condition that follows from this restated problem is not different from the one derived from the original formulation (3), provided that the comovement between asset returns satisfies the Sharpe Diagonal Model.

Note that, even when LC projects are affected by market fluctuations, the optimal investment in bucket z is unaffected by such market risk considerations, or by the risk of the investor's securities outside LC. This is because the holding of market portfolio, x_{z+1} in equation (6), optimally adjusts to account for the indirect market risk embedded in LC or any other security in the active portfolio of the investor. The optimal LC portfolio depends only on the investor's risk aversion, and the expectation and variance of the independent return of each bucket z .

We use the first order condition to recover the investor's risk aversion from those portfolio choices that constitute an interior solution. Substituting the expectation of the independent return $E[r_z^i]$ with expected return $E[R_z]$, common across investors and computed in equation (2), and substituting the expression of the variance of the independent return, $var[r_z^i]$, from equation (1), we derive our main empirical equation.²⁴ For all risk buckets z with positive positions:

$$E[R_z] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \sigma_z^2 \quad (9)$$

where:

$$\theta^i \equiv 1 + \beta_L^i E[R_m] \quad (10)$$

$$ARA^i \equiv -\frac{u''(E[c^i])}{u'(E[c^i])} \quad (11)$$

The parameter θ^i reflects the investor's assessment of the systematic component of the LC investment. It is investor and investment-specific, and constant across buckets for each investment. The parameter ARA^i corresponds to the Absolute Risk Aversion. It captures the extra expected return needed to leave the investor indifferent when taking extra risk. Such parameter refers to the local curvature of the preference function and it is not specific to the expected utility framework. We show in the Appendix that the same equation characterizes the optimal LC portfolio and the curvature of the utility function under two alternative preference specifications: 1) when investors are averse to losses in their overall wealth, and 2) when investor utility depends in a non-separable

²⁴Since our estimation procedure exploits only buckets with positive investments, we show in Subsection 7.1 that the estimated risk preferences are consistent with those implied by the forgone buckets.

way on both the overall wealth level and the income flow from specific components of the portfolio (narrow framing).

Finally, we cannot compute the Relative Risk Aversion (RRA) without observing the expected lifetime wealth of the investors.²⁵ However, for the purpose of comparing our estimates with the results from other empirical studies on relative risk aversion, we follow that literature and define the relative risk aversion parameter based solely on the income generated by investing in LC (see, for example, Holt and Laury, 2002). This *income-based RRA* is defined as follows:

$$\rho^i \equiv ARA^i \cdot I_L^i \cdot (E[R_L^i] - 1) \quad (12)$$

where I_L^i is the total investment in LC, $I_L^i = W^i \sum_{z=1}^{35} x_z^i$, and $E[R_L^i]$ is the expected return on the LC portfolio, $E[R_L^i] = \sum_{z=1}^{35} x_z^i E[R_z]$.

4 Data and Sample

Our sample covers the period between October 2007 and April 2008. Below we provide summary statistics of the investors' characteristics and their portfolio choices, and a description of the sample construction.

4.1 Investors

For each investor we observe the home address zip code, verified by LC against the checking account information, age, gender, marital status, home ownership status, and net worth, obtained through Acxiom, a third party specialized in recovering consumer demographics. Acxiom uses a proprietary algorithm to recover gender from the investor names, and matches investor names and home addresses to available public records to recover age, marital status, home ownership status, and an estimate of net worth. Such information is available at the beginning of the sample.

Table 1, panel (b), shows the demographic characteristics of the LC investors. The average

²⁵Although we cannot compute RRA, in Section 6 we show that we can infer its elasticity with respect to wealth, based on the elasticity of ARA: $\xi_{RRA,W} = \xi_{ARA,W} + 1$.

investor in our sample is 43 years old, 8 years younger than the average respondent in the Survey of Consumer Finances (SCF). As expected from younger investors, the proportion of married participants in LC (56%) is lower than in the SCF (68%). Men are over-represented among participants in financial markets, they account for 83% of the LC investors; similarly, the fraction of male respondents in the SCF is 79%. In terms of income and net worth, investors in LC are comparable to other participants in financial markets, who are typically wealthier than the median U.S. households. The median net worth of LC investors is estimated between \$250,000 and \$499,999, significantly higher than the median U.S. household (\$120,000 according to the SCF), but similar to the estimated wealth of other samples of financial investors. Korniotis and Kumar (2011), for example, estimate the wealth of clients in a major U.S. discount brokerage house in 1996 at \$270,000.

To obtain an indicator of housing wealth, we match investors' information with the Zillow Home Value Index by zip code. The Zillow Index for a given geographical area is the value of the median property in that location, estimated using a proprietary hedonic model based on house transactions and house characteristics data, and it is available at a monthly frequency. Figure 2 shows the geographical distribution of the 1,624 zip codes where the LC investors are located (Alaska, Hawaii, and Puerto Rico excluded). Although geographically disperse, LC investors tend to concentrate in urban areas and major cities. Table 1 shows the descriptive statistics of median house values on October 2007 and their variation during the sample period—October 2007 to April 2008.

4.2 Sample Construction

We consider as a single portfolio choice all the investments an individual makes within a calendar month.²⁶ The full sample contains 2,168 investors, 5,191 portfolio choices, which results in 50,254 investment-bucket observations. To compute the expected return and idiosyncratic variance of the investment-bucket in equations (2) and (1), we use as the risk free interest rate, the 3-year yield on Treasury Bonds at the time of the investment. Table 2, panel A, reports the descriptive statistics

²⁶This time window is arbitrary and modifying it does not change the risk aversion estimates. We chose a calendar month for convenience, since it coincides with the frequency of the real estate price data that we use to proxy for wealth shocks in the empirical analysis.

of the investment-buckets. The median expected return is 12.2%, with an idiosyncratic variance of 3.6%. Panel B, describes the risk and return of the investors' LC portfolios. The median portfolio expected return in the sample is 12.2%, almost identical to the expectation at the bucket level, but the idiosyncratic variance is substantially lower, 0.0054%, due to risk diversification across buckets.

Our estimation method imposes two requirements for inclusion in the sample. First, estimating risk aversion implies recovering two investor specific parameters from equation (9). Therefore, a point estimate of the risk aversion parameter can only be recovered when a portfolio choice contains more than one risk bucket.

Second, our identification method relies on the assumption that all projects in a risk bucket have the same expected return and variance. Under this assumption investors will always prefer to exhaust the diversification opportunities within a bucket, i.e., will prefer to invest \$25 in two different loans belonging to bucket z instead of investing \$50 in a single loan in the same bucket. It is possible that some investors choose to forego diversification opportunities if they believe that a particular loan has a higher return or lower variance than the average loan in the same bucket. Because investors' private insights are unobservable to the econometrician, such deviations from full diversification will bias the risk aversion estimates downwards. To avoid such bias we exclude all non-diversified components of an investment. Thus, the sample we base our analysis on includes: 1) investment components that are chosen through the optimization tool, which automatically exhausts diversification opportunities, and 2) diversified investment components that allocate no more than \$50 to any given loan.

After imposing these restrictions, the analysis sample has 2,168 investors and 3,745 portfolio choices. The descriptive statistics of the analysis sample are shown in Table 2, column 2. As expected, the average portfolio in the analysis sample is smaller and distributed across a larger number of buckets than the average portfolio in the full sample. The average portfolio expected return is the same across the two samples, while the idiosyncratic variance in the analysis sample is smaller. This is expected since the analysis sample excludes non-diversified investment components.

In the wealth analysis, we further restrict the sample to those investors that are located in zip codes where the Zillow Index is computed. This reduces the sample to 1,806 investors and 3,145

portfolio choices. This final selection does not alter the observed characteristics of the portfolios significantly (Table 2, column 3). To maintain a consistent analysis sample throughout the discussion that follows, we perform all estimations using this final subsample unless otherwise noted.

5 Risk Aversion Estimates

Our baseline estimation specification is based on equation (9). We allow for an additive error term, such that for each investor i we estimate the following equation:

$$E[R_z] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \sigma_z^2 + \varepsilon_z^i \quad (13)$$

There is one independent equation for each bucket z with a positive investment in the investor's portfolio. The median portfolio choice in our sample allocates funding to 10 buckets, which provides us with multiple degrees of freedom for estimation. We estimate the parameters of equation (13) with Ordinary Least Squares.

Figure 3 shows four examples of portfolio choices. The vertical axis measures the expected return of a risk bucket, $E[R_z]$, and the horizontal axis measures the bucket variance weighted by the investment amount, $W^i x_z^i \sigma_z^2 / n_z^i$. The slope of the linear fit is our estimate of the absolute risk aversion and it is reported on the top of each plot. The intercept is our estimate of θ^i , capturing the investor's assessment of the portfolio's systematic risk.

The error term captures deviations from the efficient portfolio due to measurement errors by investors, real or perceived private information, and differences in investors' beliefs from LC's. The OLS estimates will be unbiased as long as the error component does not vary systematically with bucket risk. We discuss and provide evidence in support of this identification assumption in Subsection 5.2.

5.1 Results

Table 3 contains the mean, standard deviation and distribution of the ARA, income-based RRA, and the parameter θ for the investors' portfolio choices.

Our first finding is that the distribution of risk aversion across households is heterogeneous and skewed. This result is in line with a number of other studies that estimate risk attitudes in a variety of settings and with various methods, ranging from surveys with lotteries on lifetime income Barsky et al. (1997), the share of risky assets in financial portfolios (Guiso and Paiella, 2008), insurance choices (Cohen and Einav, 2007), lab experiments (Choi et al., 2007) and labor supply (Chetty, 2006).

The average estimated ARA across all portfolio choices is 0.0368, with substantial heterogeneity and a left skewed distribution: the median ARA is 0.0439 and the standard deviation 0.0246.²⁷ The level and range of the ARA estimates is consistent with the estimates recovered in the laboratory. The findings in Holt and Laury (2002), for example, imply an average ARA between 0.003 for to 0.109 depending on the experiment.

Table 3 also contains the income-based RRA, a measure often reported in the microeconomics literature. The mean income-based RRA in our sample is 2.85 and its distribution is right-skewed (median 1.62). This parameter scales the measure of absolute risk aversion according to the lottery expected income; therefore, it mechanically increases with the size of the bet. The mean expected income in our setting is \$130, substantially higher than the bet in most laboratory experiments. Our results are comparable to Holt and Laury (2002), who also estimate risk aversion for agents facing large bets in the lab and find parameters consistent with an income-based RRA similar to ours, 1.2. The levels of our estimates are also qualitatively similar to the survey-based measures of Barsky et al. (1997), who find an average RRA of 4.15, and those of Chiappori and Paiella (2011), who find a mean of 4.2 and a median of 1.7. Finally, Chetty (2006) in a study based on labor supply choice, report risk premia with a mean of 0.9, which corresponds to an income-based RRA

²⁷This standard deviation overestimates the standard deviation of the true ARA parameter across investments because it includes the estimation error that results from having a limited number of buckets per portfolio choice. Following Arellano and Bonhomme (2012), we can recover the variance of the true ARA by subtracting the expected estimation variance across all portfolio choices. The calculated standard deviation of the true ARA is 0.0237, indicating that the estimation variance is small relative to the variance of risk aversion across investments. The variance of the true ARA is calculated as:

$$var [ARA^i] = var [\widehat{ARA}^i] - E [\widehat{\sigma}_{ARA^i}^2]$$

where the first term is the variance of the OLS ARA point estimates across all investments, and the second term is the average of the variance of the OLS ARA estimates across all investments.

of 1.8 in our setting.

It is important to point out that, despite being derived in a small stake environment, our estimates can be extrapolated to higher stake environments under different types of utility functions. Rabin (2000) has shown that the expected utility over wealth framework is not a good description of economic agents preferences, as the high levels of risk aversion in small stake environments found in the literature cannot be reconciled with the observable behavior of agents in environments with larger stakes. In the Appendix we show that the ARA estimated here describes the curvature of the utility function in other preference frameworks that are consistent with observed risk behavior over small and large stake gambles. In particular, Appendix A.1 describes the optimal portfolio choice in a model in which utility depends (in a non-separable way) on both overall wealth level, W , and the flow of income from specific components of the agent's portfolio, y .²⁸ In such alternate preference specifications, agents' ARA varies with, both, the level of overall wealth and the income flow generated by the gamble. This implies that the estimated level of ARA may be large for small-stake gambles (i.e., $\partial ARA(y, W)/\partial y < 0$) and yet not imply implausibly high risk aversion in large stakes environments. In the Appendix we also show that our estimate of the elasticity of ARA with respect to investor's wealth (i.e., $\frac{\partial ARA(y, W)}{\partial W} \frac{W}{ARA(y, W)}$), the focus of the next section, characterizes investors' risk attitudes, both in small and large stake environments.

The parameter θ , defined in equation (10), captures the systematic component of LC, driven by the common covariance between all LC bucket returns and the market, β_L , and the expected market risk premium. The average estimated θ is 1.086, which indicates that the average investor requires a systematic risk premium of 8.6%. The estimated θ presents very little variation in the cross section of investors (coefficient of variation 2.7%), when compared to the variation in the ARA estimates (coefficient of variation of 67%).²⁹ Finally, it is important to stress that our estimates of the ARA parameter are not derived from the investors' assessment of LC's systematic risk and

²⁸This is in line with Barberis and Huang (2001) and Barberis et al. (2006), which propose a framework where agents exhibit loss aversion over changes in specific components of their overall portfolio, together with decreasing relative risk aversion over their entire wealth. In the expected utility framework, Cox and Sadiraj (2006) propose a utility function with two arguments (income and wealth) where risk aversion is defined over income, but it is sensitive to the overall wealth level.

²⁹As with the ARA, the estimation variance is small relative to the variance across investments. The standard deviation of θ is 0.0269, while the standard deviation of θ after subtracting the estimation variance is 0.0260.

its evolution over time; instead, they are based on the marginal additional return required to take an infinitesimally greater idiosyncratic risk. It can be the case that an investor’s assessment of the systematic risk in the LC environment increases and at the same time his risk aversion, i.e. the expected return he requires to take an additional unit of idiosyncratic risk, decreases.

Table 4 presents the average and standard deviation of the estimated parameters by month. The average ARA increases from 0.032 during the first three months, to 0.039 during the last three. This average time series variation is potentially due to heterogeneity across investors as well as within investor variation, since not all investors participate in LC every month. The analysis in the next section disentangles the two sources of variation. The estimated θ s imply that the average systematic risk premium increases from 6.3% to 9.2% between the first and last three months of the sample period. Note that the LC web page provides no information on the systematic risk of LC investments. Thus, this change is solely driven by changes in investors’ beliefs about the potential systematic risk of the loans; that is, the correlation between the likelihood of default of LC loans and aggregate macroeconomic shocks, β_L , or about the expected market risk premium, $E[R_m]$. This change in investors’ assessments of the systematic risk in LC indicates that wealth shocks are potentially correlated with changes in investors’ beliefs about risk and return on financial assets. Thus, we cannot infer the elasticity of RRA to wealth by observing changes in the share of risky assets after a wealth shock, as they may be simply reflecting changes in beliefs about the underlying distribution of risky returns. The advantage of our measure of risk aversion and the proposed empirical strategy in the next section is that they do not suffer from this identification problem.

5.2 Belief Heterogeneity and Bias: The Optimization Tool

Up to now we have interpreted the observed heterogeneity of investor portfolio choices as arising from differences in risk attitudes. Such heterogeneity may also arise if investors have different beliefs about the relative risk and expected return across LC risk buckets. Note that differences in beliefs about the systematic component of returns will not induce heterogeneity in our estimates of the ARA. This type of belief heterogeneity will be captured by variations in θ across investors, and

the evidence in the previous section suggests that investors have relatively common priors about this systematic component of the returns.

However, the parameter θ will not capture heterogeneity of beliefs that affects the relative risk and expected return across buckets. This is the case if investors believe the market sensitivity of returns to be different across LC buckets, i.e. if $\beta_z^i \neq \beta_L^i$ for some $z = 1, \dots, 35$; or if investors' priors about the stochastic properties of the buckets idiosyncratic return differ from the ones computed in equations (1) and (2), i.e. $E^i [R_z] \neq E [R_z]$ or $\sigma_z^i \neq \sigma_z$ for some $z = 1, \dots, 35$. In such cases, the equation characterizing the investor's optimal portfolio is given by:

$$E [R_z] = \theta^i + [ARA^i \cdot B_\sigma^i + B_\mu^i + B_\beta^i] \cdot \frac{W^i x_z^i \sigma_z^2}{n_z^i}$$

This expression differs from our main specification equation (9) in three bias terms: $B_\sigma \equiv (\sigma_z^i / \sigma_z)^2$, $B_\mu \equiv (E [R_z] - E^i [R_z]) / (W^i x_z^i \sigma_z^2 / n_z^i)$, and $B_\beta \equiv (\beta_z^i - \beta_L^i) / (W^i x_z^i \sigma_z^2 / n_z^i)$.

Two features of the LC environment allow us to estimate the magnitude of the overall bias from these sources. First, LC posts on its website an estimate of the idiosyncratic default probabilities for each bucket. Second, LC offers an optimization tool to help investors diversify their loan portfolio. The tool constructs the set of efficient loan portfolios, given the investor's total amount in LC—i.e., the minimum idiosyncratic variance for each level of expected return. Investors then select, among all the efficient portfolios, the preferred one according to their own risk preferences. Importantly, the tool uses the same modeling assumptions regarding investors' beliefs that we use in our framework: the idiosyncratic probabilities of default are the ones posted on the website and the systematic risk is common across buckets, i.e. $\beta_z = \beta_L$.³⁰

Thus, we can measure the estimation bias by comparing, for the same investment, the ARA estimates obtained independently from two different components of the portfolio choice: the loans suggested by the tool and those chosen manually. If investors' beliefs do not deviate systematically across buckets from the information posted on LC's website and from the assumptions of the optimization tool, we should find investor preferences to be the same across the two measures.

³⁰See Appendix B.1 for the derivation of the efficient portfolios suggested by the optimization tool.

Note that our identification assumption does not require that investors agree with LC assumptions. It suffices that the difference in beliefs does not vary systematically across buckets. For example, our estimates are unbiased if investors believe that the idiosyncratic risk is 20% higher than the one implied by the probabilities reported in LC, across all buckets. Our estimates are also unbiased if investors believe that some feature of the loans, such as geographic location, is related to default and it is not reflected into the FICO score, credit history and the other credit bureau information used by LC to assign loans into risk buckets, as long as borrowers with such feature are not concentrated in one or few buckets. Note, moreover, that our test is based on investors' beliefs at the time of making the portfolio choices. These beliefs need not to be correct ex post.

For each investment, we independently compute the risk aversion implied by the component suggested by the optimization tool (Automatic buckets) and the risk aversion implied by the component chosen directly by the investor (Non-Automatic buckets). Figure 4 provides an example of this estimation. Both panels of the figure plot the expected return and weighted idiosyncratic variance for the same portfolio choice. Panel A includes only the Automatic buckets, suggested by the optimization tool. Panel B includes only the Non Automatic buckets, chosen directly by the investor. The estimated ARA using the Automatic and Non-Automatic bucket subsamples are 0.048 and 0.051 respectively for this example.

We perform the independent estimation above for all portfolio choices that have at least two Automatic and two Non-Automatic buckets. To verify that investments that contain an Automatic component are representative of the entire sample, we compare the extreme cases where the entire portfolio is suggested by the tool and those where the entire portfolio is chosen manually. The median *ARA* is 0.0440 and 0.0441 respectively, and the mean difference across the two groups is not statistically significant at the standard levels. This suggests that our focus in this subsection on investments with an Automatic component is representative of the entire investment sample.

Table 5, panel A, reports the descriptive statistics of the ARA estimated using the Automatic and the Non-Automatic buckets. The average ARA is virtually identical across the two estimations (Table 5, columns 1 and 2), and the mean difference is statistically indistinguishable from zero, with $t = 0.919$. This implies that, if there is a bias in our *ARA* estimates induced by differences

in beliefs, its mean across investments is zero. Column 3 shows the descriptive statistics of the investment-by-investment difference between the two ARA estimates. The mean is zero and the distribution of the difference is concentrated around zero, with kurtosis 11.72 (see Figure 5). This implies that the bias is close to zero not only in expectation, but investment-by-investment.

These results suggest that investors' beliefs about the stochastic properties of the loans in LC do not differ from those posted on the website in ways that invalidate our identification strategy. They also suggest that investors' choices are consistent with the assumption that the systematic component is constant across buckets. Overall, these findings validate the interpretation that the observed heterogeneity across investor portfolio decisions is driven by differences in risk preferences.

In Table 5, panels B and C, we show that the difference in the distribution of the estimated ARA from the automatic and non-automatic buckets is insignificant both during the first and second half of the sample period. This finding is key for interpreting the results in the next section, where we explore how the risk aversion estimates change in the time series with changes in housing prices. There, we interpret any observed time variation in the ARA estimates as a change in investor risk preferences over time.

Table 5, columns 4 through 6, show that the estimated risk premia, θ , also exhibit almost identical mean and standard deviations when obtained independently using the Automatic and Non-Automatic investment components. A means difference test cannot reject it is equal to zero with a $t = 0.968$. This suggests that our estimates of the risk premium are unbiased.

It is worth reiterating that these findings do not imply that investors' beliefs about the overall risk of investing in LC do not change during the sample period. On the contrary, the observed average increase in the estimated systematic risk premium in Table 4 is also observed in panels B and C of Table 5: θ increases by 2.5 percentage points between the first and second halves of the sample. The results in Table 5 indicate that changes in investors' beliefs are fully accounted for by a common systematic component across all risk buckets and changes in interest rates set by LC and, thus, do not bias our risk aversion estimates.

6 Risk Aversion and Wealth

This section explores the relationship between investors' risk taking behavior and wealth. We estimate the elasticity of ARA with respect to wealth, and use it to obtain the elasticity of RRA with respect to wealth, based on the following expression:

$$\xi_{RRA,W} = \xi_{ARA,W} + 1, \tag{14}$$

where $\xi_{RRA,W}$ and $\xi_{ARA,W}$ refer to the wealth elasticities of RRA and ARA, respectively. For robustness, we also estimate the elasticity of the income-based RRA in equation (12), $\xi_{\rho,W}$.

We exploit the panel dimension of our data and estimate these elasticities, both, for a given investor, in the time series, and in the cross section of investors. We find that investor specific RRA increases after experiencing a negative wealth shock; that is, the preference function exhibits decreasing RRA. In the cross section, we find that wealthier investors exhibit lower ARA and higher RRA when choosing their portfolio of loans within LC; we refer to these elasticity estimates with the superscript xs to emphasize that they do not represent a feature of individual preferences (i.e., $\xi_{ARA,W}^{xs}$, $\xi_{RRA,W}^{xs}$, $\xi_{\rho,W}^{xs}$). The contrasting signs of the investor-specific and cross sectional wealth elasticities indicate that preferences and wealth are not independently distributed across investors and inferring the elasticity of RRA to wealth from the cross section would lead to incorrect inferences.

6.1 Wealth and Wealth Shock Proxies

Below, we describe our proxies for wealth in the cross section of investors, and for wealth shocks in the time series. Since the bulk of the analysis uses housing wealth as a proxy for investor wealth, we focus the discussion in this section on the subsample of investors that are home-owners.³¹

³¹None of the results in this section is statistically significant in the subsample of investors that are renters. This is expected since housing wealth and total wealth are less likely to be correlated for renters, particularly in the time series. However, this is also possibly due to lack of power, since only a small fraction of the investors in our sample are renters.

6.1.1 Cross Section

We use Acxiom’s imputed net worth as of October 2007 as a proxy for wealth in the cross section of investors. As discussed in Section 4, Acxiom’s imputed net worth is based on a proprietary algorithm that combines names, home address, credit rating, and other data from public sources. To account for potential measurement error in this proxy, we use a separate indicator for investor wealth in an errors-in-variable estimation: median house price in the investor’s zip code at the time of investment. Admittedly, house value is an imperfect indicator wealth; it does not account for heterogeneity in mortgage level or the proportion of wealth invested in housing. Nevertheless, as long as the measurement errors are uncorrelated across the two proxies, a plausible assumption in our setting, the errors-in-variable estimation provides an unbiased estimate of the cross-sectional elasticity of risk aversion to wealth.

The errors-in-variables approach works in our setting because risk preferences are obtained independently from wealth. If, for example, risk aversion were estimated from the share of risky and riskless assets in the investor portfolio, this estimate would inherit the errors in the wealth measure. As a result, any observed correlation between risk aversion and wealth could be spuriously driven by measurement errors. This is not a concern in our exercise.

6.1.2 Wealth Shocks

House values dropped sharply during our sample period. Since housing represents a substantial fraction of household wealth in the U.S., this decline implied an important negative wealth shock for home-owners.³² We use this source of variation, to estimate the wealth elasticity of investor-specific risk aversion in the subsample of home-owners that invest in LC. In this subsample the average zip code house price declines 4% between October 2007 and April 2008.³³

The drop in house value is an incomplete measure of the change in the investor overall wealth. It is important, then, to analyze the potential estimation bias introduced by this measurement error.

³²According to the Survey of Consumer Finances of 2007, the value of the primary residence accounts for approximately 32% of total assets for the median U.S. family (see Bucks et al., 2009).

³³In addition, the time series house price variation is heterogeneous across investors: the median house price decline is 3.6%.

Any time-invariant measurement error or unobserved heterogeneity across investors is captured by the investor fixed effect and does not affect our elasticity estimates. However, the estimate of the wealth elasticity of risk aversion will be biased if the percentage change in wealth is different from the drop in house values. If the drop in house prices is disproportionately large relative to the change in overall wealth, our estimates of the elasticity will be biased towards zero. And, alternatively, if the percentage decline in house values underestimates the change in the investor’s total wealth, then the wealth elasticity of risk aversion will be overestimated (in absolute value). Finally, if the measurement error in the computation of the wealth shock is not systematic, we will estimate the elasticity with the classic attenuation bias, in which case our estimates provide a lower bound for the elasticities of risk aversion to wealth. In subsection 6.3, we analyze how our conclusions are affected under different types of measurement error.

6.2 Cross-Sectional Evidence

We begin by exploring non-parametrically the relationship between the risk aversion estimates and our two wealth proxies for the cross section of home-owner investors in our sample. Figure 6 plots a kernel-weighted local polynomial smoothing of the risk aversion measure. The horizontal axis measures the (log) net worth and the (log) median house price in the investor’s zip code at the time of the portfolio choice. ARA is decreasing in both wealth proxies, while income-based RRA is increasing.

Turning to parametric evidence, we estimate the cross sectional elasticity of ARA to wealth using the following regression:

$$\ln(ARA_i) = \beta_0 + \beta_1 \ln(NetWorth_i) + \omega_i. \tag{15}$$

The left hand side variable is investor i ’s average (log) ARA, obtained by averaging the ARA estimates recovered from the investor’s portfolio choices during our sample period. The right-hand side variable is investor i ’s imputed net worth. Thus, the estimated β_1 corresponds to the cross-sectional wealth elasticity of ARA, $\xi_{ARA,W}^{xs}$.

To account for measurement error in our wealth proxy we estimate specification (15) in an errors-in-variables model by instrumenting imputed net worth with the average (log) house value in the zip code of residence of investor i during the sample period. Since the instrument varies only at the zip code level, in the estimation we allow the standard errors in specification (15) to be clustered by zip code.

Table 6 shows the estimated cross sectional elasticities with OLS and the errors-in-variables model (panels A and B respectively). Our preferred estimates from the errors-in-variables model indicate that the elasticity of ARA to wealth in the cross section is -0.059 and statistically significant at the 1% confidence level (Table 6, column 1). The non-parametric relationship is confirmed: wealthier investors exhibit a lower ARA. The OLS elasticity estimate is biased towards zero. This attenuation bias is consistent with classical measurement error in the wealth proxy.

The estimated ARA elasticity and equation (14) imply that the wealth-based RRA elasticity to wealth is positive, $\widehat{\xi}_{RRA,W}^{xs} = 0.94$. Column 2 shows the result of estimating specification (15) using the income-based RRA as the dependent variable. The income-based RRA increases with investor wealth in the cross section, and the point estimate, 0.12, is also significant at the 1% level. The sign of the estimated elasticity coincides with that implied by the ARA elasticity. Overall, the results consistently indicate that the RRA is larger for wealthier investors in the cross section.

6.3 Within-Investor Estimates

The above cross sectional elasticity, can be taken to represent the investors' elasticity of risk aversion to wealth only under strong assumptions. Namely, when the distributions of wealth and preferences in the population are independent.³⁴ In this Section we estimate the ARA elasticity using within-investor time series variation in wealth:

$$\ln(ARA_{it}) = \alpha_i + \beta_2 \ln(HouseValue_{it}) + \omega_{it}. \quad (16)$$

³⁴Chiappori and Paiella (2011) formally prove that any within-investor elasticity of risk aversion to wealth can be supported in the cross section by appropriately picking such joint distribution.

The left-hand side variable is the estimated ARA for investor i in month t . The right-hand side variable of interest is the (log) median house value of the investor’s zip code during the month the risk aversion estimate was obtained (i.e., the month the investment in LC takes places). The right-hand side of specification (16) includes a full set of investor dummies as controls. These investor fixed effects (FE) account for all cross sectional differences in risk aversion levels. Thus, the elasticity β_2 recovers the sensitivity of ARA to investor-specific shocks to wealth.

By construction, the parameter β_2 can be estimated only for the subsample of investors that choose an LC portfolio more than once in our sample period. Although the average number of portfolio choices per investor is 1.8, the median investor chooses only once during our analysis period. This implies that the data over which we obtain the within investor estimates using (16) comes from less than half of the original sample. To insure that the results below are representative for the full investor sample, we also show the results of estimating specification (16) without the investor FE to corroborate that the conclusions of the previous section are unchanged when estimated on the subsample of investors that chose portfolios more than once.

Table 7 reports the parameter estimates of specification (16), before and after including the investor FE (Panels A and B respectively). The FE results represent our estimated wealth elasticities of ARA, $\xi_{ARA,W}$. The sign of the estimated within-investor elasticity of ARA to wealth (column 1) is the same as in the cross section: absolute risk aversion is decreasing in investor wealth.

Equation (14) and the estimated wealth elasticity of ARA imply a negative wealth-based RRA to wealth changes for a given investor, $\xi_{RRA,W}$, of -1.82. Column 2 reports the result of estimating specification (16) using the income-based RRA as the dependent variable. The point estimate, -4.18, also implies a negative relationship between this alternative measure of RRA and wealth. These results consistently suggest that investors’ utility function exhibits Decreasing Relative Risk Aversion.

Measurement error in our proxy for wealth is unlikely to change this conclusion. Classical measurement error would imply that the point estimate is biased towards zero; this estimate is therefore a lower bound (in absolute value) for the actual wealth elasticity of risk aversion. On the contrary, the (absolute value) of the elasticity could be overestimated if the percentage decline

in house values underestimates the change in the investor’s total wealth. However, for error in measurement to account for the sign of the elasticity, the overall change in wealth has to be three times larger than the percentage drop in house value.³⁵ This is unlikely in our setting since stock prices dropped 10% and investments in bonds had a positive yield during our sample period.³⁶ Therefore, even if measurement error biases the numerical estimate, it is unlikely to affect our conclusions regarding RRA decreasing with wealth.

The observed positive relationship between investor RRA and wealth in the cross section from the previous section changes sign once one accounts for investor preference heterogeneity. The comparison of the estimates with and without investor FE of panels A and B in Table 7 confirms it. This implies that investors preferences and wealth are not independently distributed in the cross section. Investors with different wealth levels may have different preferences, for example, because more risk averse individuals made investment choices that made them wealthier. Alternatively, an unobserved investor characteristic, such as having more educated parents, may cause an investor to be wealthier and also to be more risk averse. The results indicate that characterizing empirically the elasticity of risk aversion to wealth requires, first, accounting for such heterogeneity.

7 Consistency of Preferences

In this section we show that the estimated *level* and wealth *elasticity* of risk aversion consistently extrapolate to other investors’ decisions. For that, we exploit the different dimensions of the investment decision in LC: the total amount to invest in LC, the loans to include in the portfolio, and the portfolio allocation across these loans.

³⁵We estimate the elasticity of ARA with respect to changes in house value to be -2.82 . Let W be overall wealth and H be house value, then: $\xi_{ARA,W} = \frac{d \ln ARA}{d \ln W} = -2.82 \cdot \frac{d \ln H}{d \ln W}$. The wealth elasticity of RRA is positive only if $\xi_{ARA,W} > -1$, which requires $\frac{d \ln W}{d \ln H} > 2.82$.

³⁶Between October 1, 2007 and April 30, 2008 the S&P 500 Index dropped 10% and the performance of U.S. investment grade bond market was positive —Barclays Capital U.S. Aggregate Index increased approximately 2%.

7.1 Foregone Risk Buckets

The investor-specific ARA is estimated in Section 5 based on the allocation of funds across the risk buckets included in her portfolio. Yet, investors select in their portfolio only a subset of the buckets available. In this subsection we show that including the *foregone* buckets in the investor’s portfolio would lower her expected utility given her estimated ARA. Thus, investors’ estimated *level* of risk aversion is consistent with the preferences revealed by their selection of loans.

The median investor in the analysis sample assigns funds to 10 out of 35 risk buckets (see Table 2, panel B). Our empirical specification (13) characterizes the allocation of the median investment among these 10 buckets without using the corresponding equations describing the choice of the 25 foregone buckets. We use these conditions to develop a consistency test for investors’ choices.

For each investor i , let A^i be the set of all risk buckets with positive positions—i.e., $A^i = \{z \leq 35 | x_z^i \geq 25\}$. The optimal portfolio model described in Section 3, predicts that, for all foregone risk buckets $z \notin A^i$, the first order condition (9), evaluated at the minimum investment amount per project of \$25, is negative—i.e. the minimum investment constraint is binding. The resulting linearized condition for all $z \notin A^i$ is:

$$foc_{foregone} = E[R_z] - \theta^i - ARA^i \cdot 25 \cdot \sigma_z^2 < 0$$

We test this prediction by calculating $foc_{foregone}$ for every foregone bucket using the parameters $\{\theta = \hat{\theta}^i, ARA^i = \widehat{ARA}^i\}$ estimated with specification (13). To illustrate the procedure, suppose that investor i chooses to allocate funds to 10 risk buckets. From that choice we estimate a constant $\hat{\theta}^i$ and an absolute risk aversion \widehat{ARA}^i using specification (13). For each of the 25 foregone risk buckets we calculate $foc_{foregone}$ above. Then we repeat the procedure for each investment in our sample and test whether $foc_{foregone}$ is negative.

Using the procedure above we calculate 85,366 values for $foc_{foregone}$. The average value for the first order condition evaluated at the foregone buckets is -0.000529 , with a standard deviation of 0.0000839 . This implies that the 95% confidence interval for $foc_{foregone}$ is $[-0.00069, -0.00036]$. The null hypothesis that the mean is equal to zero is rejected with a $t = -6.30$. If we repeat this

test investment-by-investment, the null hypothesis that mean of $foc_{foregone}$ is zero is rejected for the median investment with a $t = -1.99$.

These results confirm that the risk preferences recovered from the investors' portfolio choices are consistent with the risk preferences implied by the foregone investment opportunities in LC.

7.2 Amount Invested in LC

In this subsection we test whether the risk attitudes exhibited by investors when choosing their portfolio of loans within LC consistently extrapolate to their decision of how much to invest in the overall lending platform. Our model in Section 3 delivers the following testable implications (see Appendix B.2). First, the investor's total amount invested in LC will decrease in her *level* of Absolute Risk Aversion with elasticity -1 . Second, concerning the cross-sectional and within-investor *elasticities* of risk aversion to wealth, when relative risk aversion decreases (increases) in wealth, then the share of wealth invested in LC will increase (decrease) in wealth. We can use these predictions, both, to provide an independent validation for the estimates obtained in Sections 5 and 6, and to explore the connection between investors' risk preferences across different types of choices.

Figure 7 shows non-parametrically the relationship between the risk aversion estimates and the overall amount invested in LC for each investor in our sample. The horizontal axis measures the ARA estimated using specification (13) while the plot corresponds to the kernel-weighted local polynomial smoothing of the log of total investment in LC, and its 95% confidence interval. Those agents who exhibit higher ARA in their allocation across risk buckets within LC, consistently invest less in the lending platform. The implied elasticity of investment in LC to the estimated ARA, estimated via OLS in the cross section of investors, is -0.88 . The standard deviation of the estimated elasticity is 0.057, which implies that the hypothesis that the elasticity is equal from -1 cannot be rejected at confidence levels below 4%. These results confirm that the investors' risk attitudes recovered from their portfolio choices within LC are consistent with the amount they invested in the lending platform.

We test the implications concerning the *elasticities* of risk aversion to wealth by estimating

specifications (15) and (16) using the (log) amount invested in LC as the dependent variable. Tables 6 and 7 (column 3) report the estimated cross sectional and within-investor elasticities.

We find that the investment amount is increasing with investor wealth in the cross section (Table 6, column 3). The elasticity is smaller than one, which suggests that the ratio of the investment to wealth is decreasing for wealthier investors. These estimates are consistent with the decreasing ARA and increasing RRA cross sectional elasticities reported in Table 6. That is, agents that exhibit larger risk aversion in their portfolio choice within LC are also characterized by lower risk tolerance when choosing how much to invest in the program.

The estimated wealth elasticity of total investment in LC is positive and greater than one when we add investor fixed effects (Table 6 column 3). This implies that, for a given investor, the ratio of investment to wealth is increasing in wealth. These results mirror those in the previous subsection concerning the estimates of the elasticity of investor specific ARA with respect to changes in wealth. We can therefore conclude that changes in wealth have the same qualitative effect on the investors' attitudes towards risk, both, when deciding her portfolio within LC and when choosing how much to allocate in LC relative to other investment opportunities. The findings in this subsection confirm the conclusion that investors' utility function exhibits decreasing relative risk aversion. Our results also suggest that preference parameters obtained from marginal choices can plausibly explain decision making behavior in broader contexts.

8 Conclusion

In this paper we have estimated risk aversion parameters and their elasticity to wealth based on the actual financial decisions of a panel of U.S. investors participating in a person-to-person lending platform. We find a large degree of heterogeneity and skewness in risk attitudes: the average absolute risk aversion is 0.0368, while the average income-based RRA is 2.85 and its median is 1.62.

An important feature of our methodology is that we estimate risk aversion from a first order condition that reflects the additional expected return an investor requires to take additional

idiosyncratic risk. This approach provides a local estimate of absolute risk aversion that is independent from a particular functional form. It generates consistent estimates for the curvature of the utility function under expected utility, but also alternative preference specifications, such as loss aversion and narrow framing, that can reconcile the observed high levels of risk aversion in small stake environments with the observable behavior of agents in environments with larger stakes (Rabin, 2000).

In focusing on idiosyncratic risk our approach is closely related to that of the microeconomics literature that studies risk attitudes using insurance data (Cohen and Einav, 2007; Barseghyan et al., 2013; Einav et al., 2012), but also to the study of risk aversion in the lab and in the field (Holt and Laury, 2002, Choi et al., 2007), and other non-financial real life settings (Jullien and Salanie, 2000; Bombardini and Trebbi, 2013; Post et al., 2008). Despite the different settings, subjects and methods, our findings on the distribution and level of risk attitudes in the population are quite similar to these studies and to other work based on overall rather than idiosyncratic risk (Barsky et al., 1997; Guiso and Paiella, 2008; among others).

Our study also estimates the elasticity of risk aversion to wealth, a fundamental parameter in many asset pricing and macroeconomic theories. We find that investors become more risk averse after a negative housing wealth shock, consistent with Decreasing Relative Risk Aversion and theories of habit formation and incomplete markets.

An appealing feature of our setting is that it allows us to study the behavior of real investors and at the same time, the rules and features of the website let us control for the effect of investors' beliefs about the risk and return of the loans. Moreover, since we observe the same investors making multiple portfolio choices, we can build a panel of risk aversion estimates and, for each individual, estimate the elasticity of risk aversion to wealth separately from the effect of heterogeneity in risk attitudes across investors. The paper provides empirical evidence that these issues are important. The opposite sign of the panel and the cross sectional evidence on the elasticity of risk aversion to wealth indicates that ignoring the effect of heterogeneity in investors' risk attitudes can lead to a severe bias in the estimates and, in our case, to conclude in favor of increasing relative risk aversion when it is in fact decreasing. Our results also show that the housing wealth shocks we use

in the analysis were accompanied by a substantial increase in the investors' assessment of the loans' systematic risk over the sample period. Thus, measuring risk aversion based on the share of risky assets in investors' portfolio and ignoring changes in their beliefs would have lead to overestimating the elasticity of RRA to wealth, since part of the reallocation toward safer portfolios was not due to increased risk aversion, but rather to an increased perception of the riskiness of the securities.

Finally, some issues that interest this literature in general are also worth discussing. Are the parameters we have estimated also valid descriptors of risk taking behavior in other contexts? This is an empirical question. Many studies of the same subjects across different domains are needed to reach robust conclusions. The evidence collected so far points both to reasons for caution and optimism. While the psychology literature argues there is very little commonality in the way individuals make decisions under uncertainty in different contexts, the economics literature finds evidence that, despite the heterogeneity, individuals do indeed make consistent choices across different domains. In particular, Einav et al. (2012) examine the workplace-based benefit choices that Alcoa employees make concerning their 401(k) asset allocations and different types of insurance and investigate the stability in ranking across contexts of an individual's willingness to bear risk relative to his peers. They find that individual choices are positively correlated across domains and the correlation is stronger the more similar are the domains.

To conclude, one important message of our paper is that it is important to take heterogeneity in investors' risk attitudes into account when estimating the relationship of risk aversion to wealth. A second message is the importance of controlling for changes in beliefs about risk and returns that might be correlated to the wealth shocks and lead to a bias. While the distribution and level of the risk aversion parameters found by the micro literature are remarkably similar across a variety of other settings, subjects and elicitation and estimation methods, more studies are needed to explore the stability of risk aversion parameters across different contexts.

References

Arellano, Manuel, and Stephane Bonhomme (2012) 'Identifying Distributional Characteristics in Random Coefficients Panel Data Models.' *Review of Economic Studies* 79(3), 987–1020

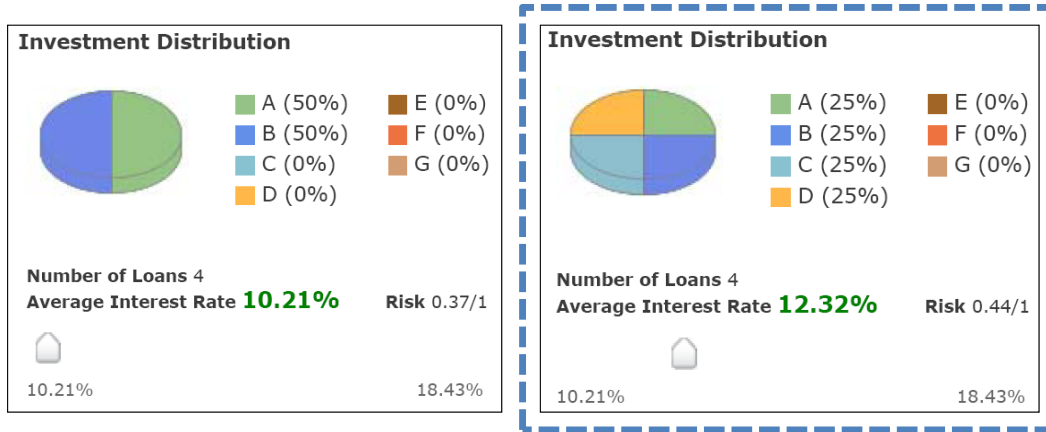
- Barberis, Nicholas, and Ming Huang (2001) ‘Mental Accounting, Loss Aversion, and Individual Stock Returns.’ *The Journal of Finance* 56(4), 1247–1292
- Barberis, Nicholas, Ming Huang, and Richard H. Thaler (2006) ‘Individual preferences, monetary gambles, and stock market participation: A case for narrow framing.’ *The American Economic Review* 96(4), 1069–1090
- Barseghyan, Levon, Francesca Molinari, Ted O’Donoghue, and Joshua Teitelbaum (2013) ‘Are Risk Preferences Stable Across Contexts? Evidence from Insurance Data.’ *The American Economic Review*
- Barsky, Robert B., F. Thomas Juster, Miles S. Kimball, and Matthew D. Shapiro (1997) ‘Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study.’ *The Quarterly Journal of Economics* 112(2), 537–579
- Blume, Marshall, and Irwin Friend (1975) ‘The Asset Structure of Individual Portfolios and Some Implications for Utility Functions.’ *The Journal of Finance* 30(2), 585–603
- Bombardini, Matilde, and Francesco Trebbi (2013) ‘Risk Aversion and Expected Utility Theory: an Experiment with Large and Small Stakes.’ *Journal of the European Economic Association*
- Brunnermeier, Markus, and Stefan Nagel (2008) ‘Do Wealth Fluctuations Generate Time-Varying Risk Aversion? Micro-evidence on Individuals.’ *The American Economic Review* 98(3), 713–36
- Bucks, Brian, Arthur Kennickel, Traci Mach, and Kevin Moore (2009) ‘Changes in U.S. Family Finances from 2004 to 2007: Evidence from the Survey of Consumer Finances.’ *Federal Reserve Bulletin* 95, A1–A55
- Calvet, Laurent, and Paolo Sodini (2009) ‘Twin Picks: Disentangling the Determinants of Risk-Taking in Household Portfolios.’ *Working Paper*
- Calvet, Laurent E., John Y. Campbell, and Paolo Sodini (2009) ‘Fight or Flight? Portfolio Rebalancing by Individual Investors.’ *The Quarterly Journal of Economics* 124(1), 301–348
- Campbell, John, and John Cochrane (1999) ‘By Force of Habit: A Consumption Based Explanation of Aggregate Stock Market Behavior.’ *Journal of Political Economy* 107, 205–251
- Chetty, Raj (2006) ‘A New Method of Estimating Risk Aversion.’ *The American Economic Review* 96(5), 1821–1834
- Chiappori, Pierre-Andre, Amit Gandhi, Bernard Salanie, and Francois Salanie (2008) ‘You Are What You Bet: Eliciting Risk Attitudes from Horse Races.’ *Working Paper*
- (2009) ‘Identifying Preferences under Risk from Discrete Choices.’ *American Economic Review* 99(2), 356 – 362
- Chiappori, Pierre-Andre, and Monica Paiella (2011) ‘Risk Aversion is Constant: Evidence from Panel Data.’ *Journal of the European Economic Association* 9(6), 1021–1052

- Choi, Syngjoo, Raymond Fisman, Douglas Gale, and Shachar Kariv (2007) ‘Consistency and Heterogeneity of Individual Behavior under Uncertainty.’ *The American Economic Review* 97(5), 1921–1938
- Cicchetti, Charles, and Jeffrey Dubin (1994) ‘A Microeconomic Analysis of Risk Aversion and the Decision to Self-Insure.’ *Journal of Political Economy* 102(11), 169–186
- Cohen, Alma, and Liran Einav (2007) ‘Estimating Risk Preferences from Deductible Choice.’ *The American Economic Review* 97(3), 745–788
- Cohn, Richard A., Wilbur G. Lewellen, Ronald C. Lease, and Gary G. Schlarbaum (1975) ‘Individual Investor Risk Aversion and Investment Portfolio Composition.’ *The Journal of Finance* 30(2), 605–620
- Cox, James, and Vjollca Sadiraj (2006) ‘Small- and Large-stakes Risk Aversion: Implications of Concavity Calibration for Decision Theory.’ *Games and Economic Behavior* 56, 45–60
- Einav, Liran, Mark R. Cullen, Amy Finkelstein, and Iuliana Pascu (2012) ‘How General are Risk Preferences? Choice under Uncertainty under Different Domains.’ *The American Economic Review* 21(1), 415–448
- Gomes, Francisco, and Alexander Michaelides (2008) ‘Asset Pricing with Limited Risk Sharing and Heterogeneous Agents.’ *The Review of Financial Studies* 21(1), 415–448
- Guiso, Luigi, and Monica Paiella (2008) ‘Risk Aversion, Wealth, and Background Risk.’ *Working Paper*
- Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2011) ‘Time Varying Risk Aversion.’ *Working Paper*
- Guvenen, Fatih (2009) ‘A Parsimonious Macroeconomic Model for Asset Pricing.’ *Econometrica* 77(6), 1711–1750
- Harrison, Glenn, Morten Lau, and Elisabet Rutstrom (2007) ‘Estimating Risk Attitudes in Denmark: A Field Experiment.’ *Scandinavian Journal of Economics* 109(2), 341–368
- Holt, Charles A., and Susan K. Laury (2002) ‘Risk Aversion and Incentive Effects.’ *The American Economic Review* 92(5), 1644–1655
- Iyer, Rajkamal, Asim Khwaja, Erzo Luttmer, and Kelly Shue (2011) ‘Inferring Asset Quality: Determining Borrower Creditworthiness in Peer-to-Peer Lending Markets.’ *Working Paper*
- Jullien, Bruno, and Bernard Salanie (2000) ‘Estimating Preferences Under Risk: The Case of Racetrack Bettors.’ *The Journal of Political Economy* 108(3), 503–530
- Kocherlakota, Narayana (1996) ‘The Equity Premium: It’s Still a Puzzle.’ *Journal of Economic Literature* 34(1), 42–71
- Korniotis, George, and Alok Kumar (2011) ‘Do Older Investors Make Better Investment Decisions?’ *Review of Economics and Statistics* 93(1), 244–265

- Lin, Mingfen, Nagpurnanand Prabhala, and Siva Viswanathan (2012) ‘Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending.’ *Management Science*
- Morin, Roger-A., and A. Fernandez Suarez (1983) ‘Risk Aversion Revisited.’ *The Journal of Finance* 38(4), 1201–1216
- Post, Thierry, Martijn J. van den Assem, Guido Baltussen, and Richard H. Thaler (2008) ‘Deal or No Deal? Decision Making under Risk in a Large-Payoff Game Show.’ *American Economic Review* 98(1), 38–71
- Rabin, Matthew (2000) ‘Risk Aversion and Expected-Utility Theory: A Calibration Theorem.’ *Econometrica* 68(5), 1281–1292
- Seru, Amit, Noah Stoman, and Tyler Shumway (2010) ‘Learning by Trading.’ *Review of Financial Studies* 23(2), 705–739
- Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen (2010) ‘Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam.’ *American Economic Review* 100(1), 557–571
- Treynor, Jack, and Fischer Black (1973) ‘How to Use Security Analysis to Improve Portfolio Selection.’ *Journal of Business* 46(1), 66–86

Account Balance \$100.00

* Investment Amount \$25 minimum



(a) Screen 1: Interest rate and Normalized Variance. Slider

My Order Summary

4 loans for a total of \$100 (\$0.00 Available)
 Risk Level: **0.44/1**
 Average Interest Rate: **12.32%**

A (25%) B (25%) C (25%) D (25%) E (0%) F (0%) G (0%)

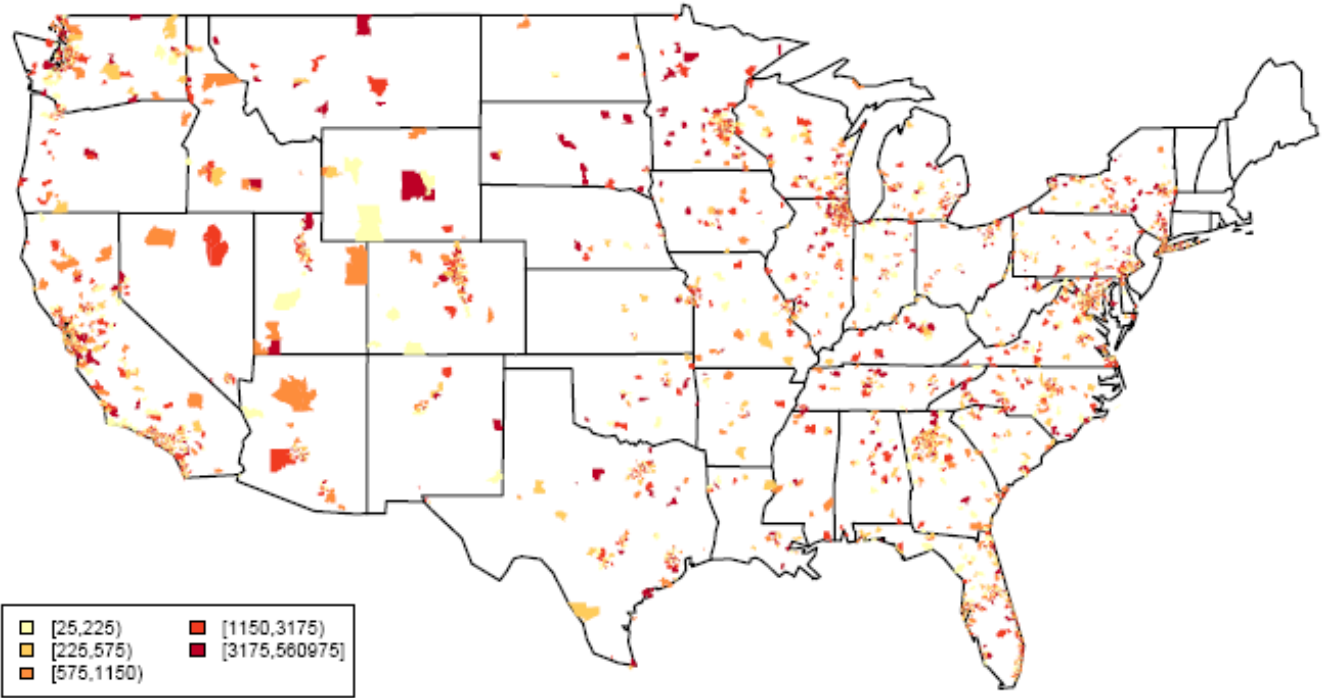
Start Over Add More Notes Buy Notes

Investment Amount	Title	Loan Amount	Interest Rate	Connections	Left to Fund	Time Left
<input type="text" value="\$25"/>	Bye Bye Wells Fargo	\$9,200	A5: 8.94%		\$1,900	11 days
<input type="text" value="\$25"/>	Christmas fund	\$15,000	B3: 11.83%		\$13,050	10 days
<input type="text" value="\$25"/>	Citi Bank sucks at 29.99% rate	\$10,000	C1: 12.87%		\$8,750	12 days
<input type="text" value="\$25"/>	NEXT LEVEL UPGRADE	\$7,500	D4: 15.65%		\$3,800	5 days

(b) Screen 2: Suggested Portfolio Summary

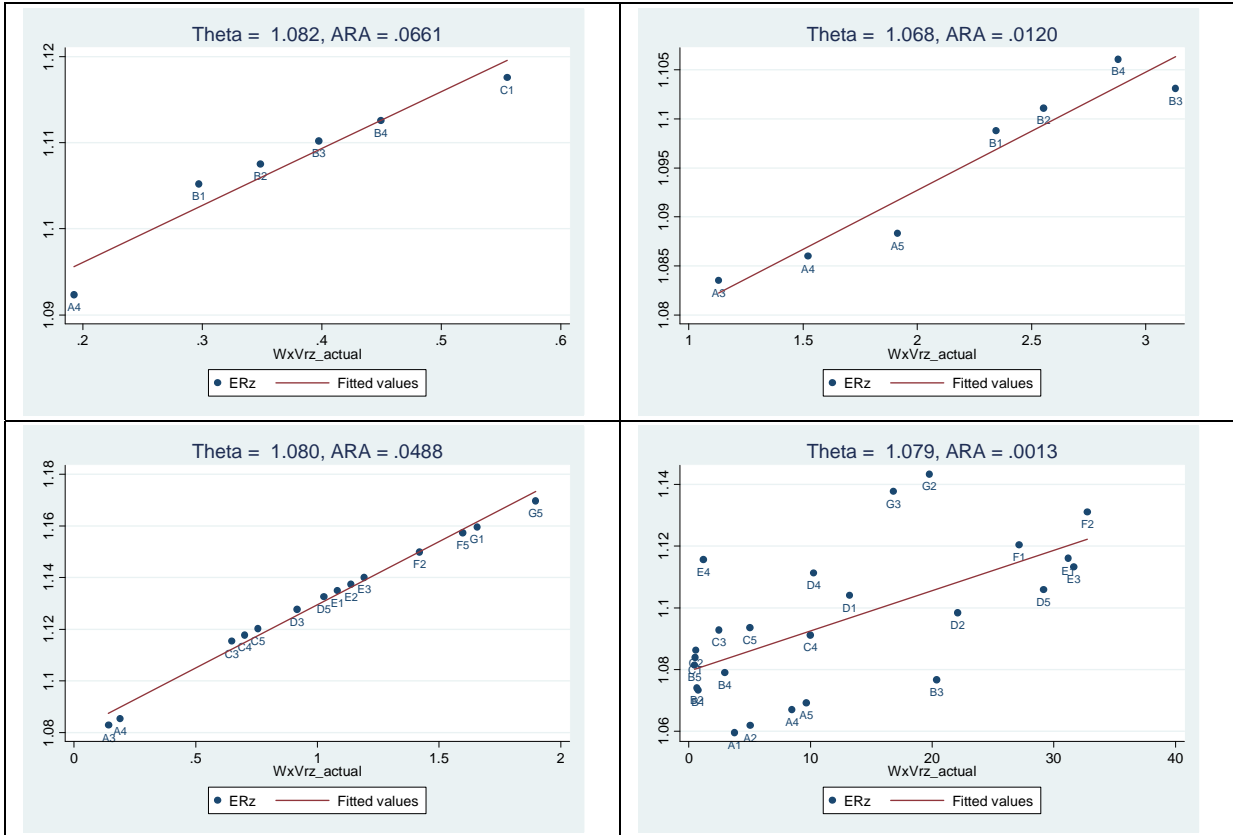
The website provides an optimization tool that suggests the efficient portfolio of loans for the investor's preferred risk return trade-off, under the assumption that loans are uncorrelated with each other and with outside investment opportunity. The risk measure is the variance of the diversified portfolio divided by the variance of a single investment in the riskiest loan available (as a result it is normalized to be between zero and one). Once a portfolio has been formed, the investor is shown the loan composition of her portfolio on a new screen that shows each individual loan (panel b). In this screen the investor can change the amount allocated to each loan, drop them altogether, or add others.

Figure 1: Portfolio Tool Screen Examples for a \$100 Investment



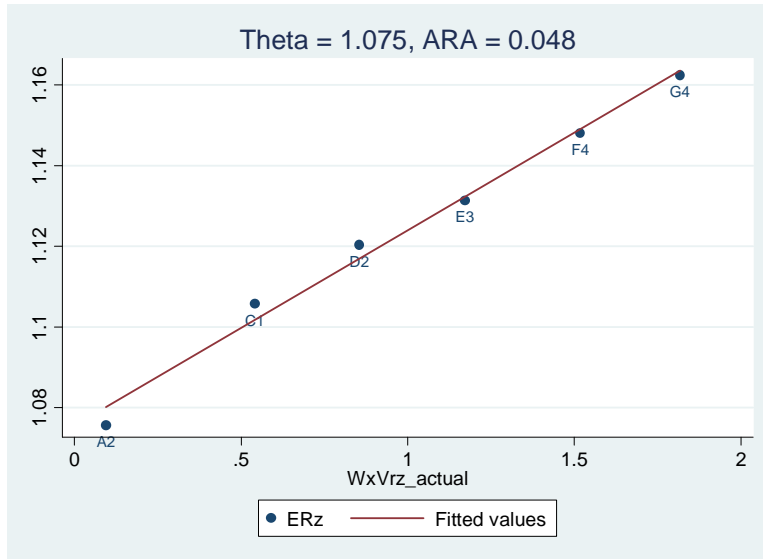
In color: zip codes with Lending Club investors. The color intensity reflects the total dollar amount invested in LC by investors in each zip code.

Figure 2: Geographical Distribution of Lending Club Investors

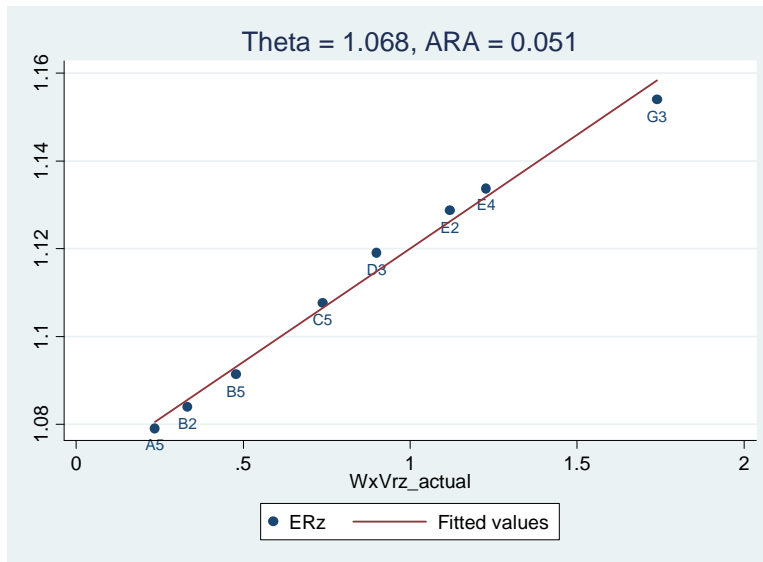


Each plot represents one investment in our sample. The plotted points represent the risk and weighted return of each of the buckets that compose the investment. The dots are labeled with the corresponding risk classification of the bucket. The vertical axis measures the expected return of a risk bucket, and the horizontal axis measures the bucket variance weighted by the total investment in that bucket. The slope of the linear fit is our estimate of the absolute risk aversion (ARA). The intersection of this linear fit with the vertical axis is our estimate for the risk premium (θ).

Figure 3: Examples of Risk Return Choices and Estimated RRA



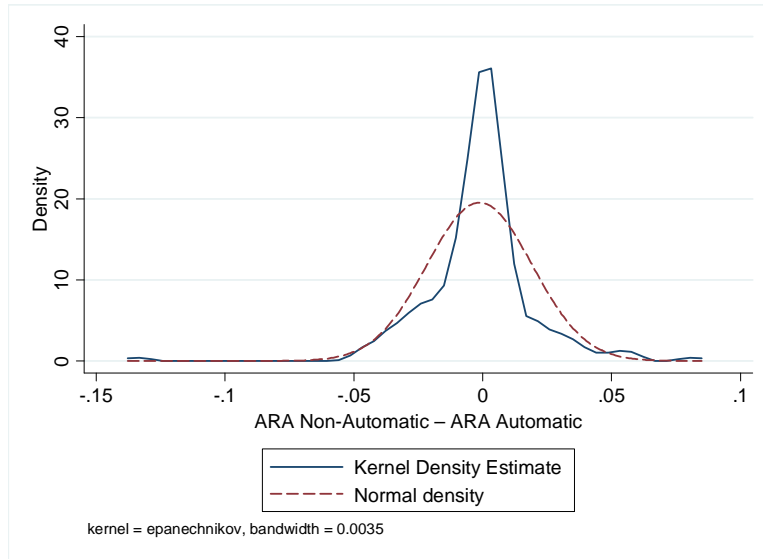
(a) Automatic Buckets



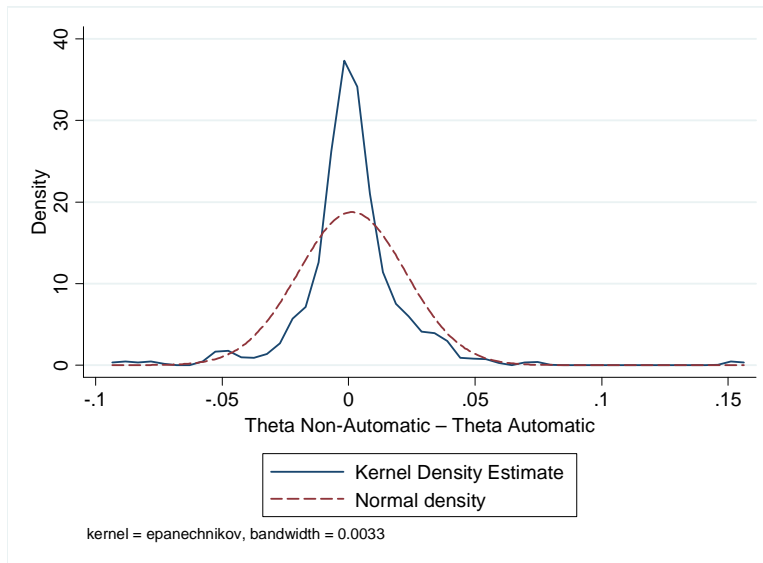
(b) Non-Automatic Buckets

Both plots represent allocations to risk buckets of the same actual investment. As in Figure 3, the plotted points represent the risk and weighted return of each of the buckets that compose the investment. Panel (a) shows the buckets that were chosen by the portfolio tool (*Automatic*), and panel (b) shows buckets directly chosen by the investor (*Non-Automatic*). The slope of the linear fit represents the absolute risk aversion (ARA), and its intersection with the vertical axis represents the risk premium (θ).

Figure 4: Risk Aversion Estimation Example Using Automatic and Non-Automatic Buckets



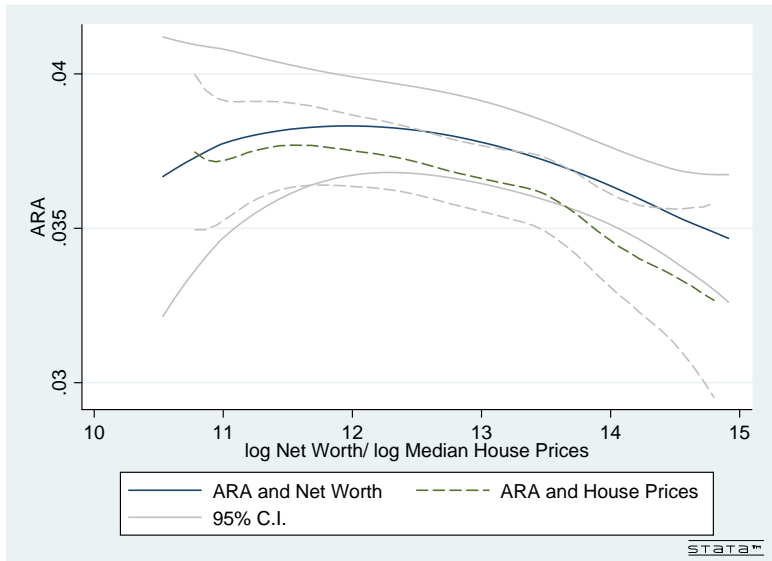
(a) ARA: Automatic and Non-Automatic Choices



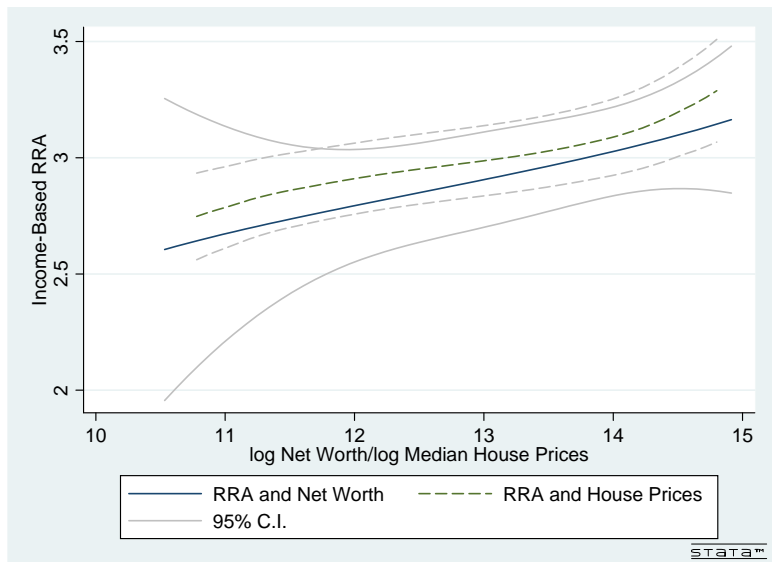
(b) θ : Automatic and Non-Automatic Choices

Difference between the estimate for ARA and θ obtained using buckets chosen directly by investors (*Non-Automatic*) and buckets suggested by optimization tool (*Automatic*), for the same investment.

Figure 5: Investment-by-Investment Bias Distribution



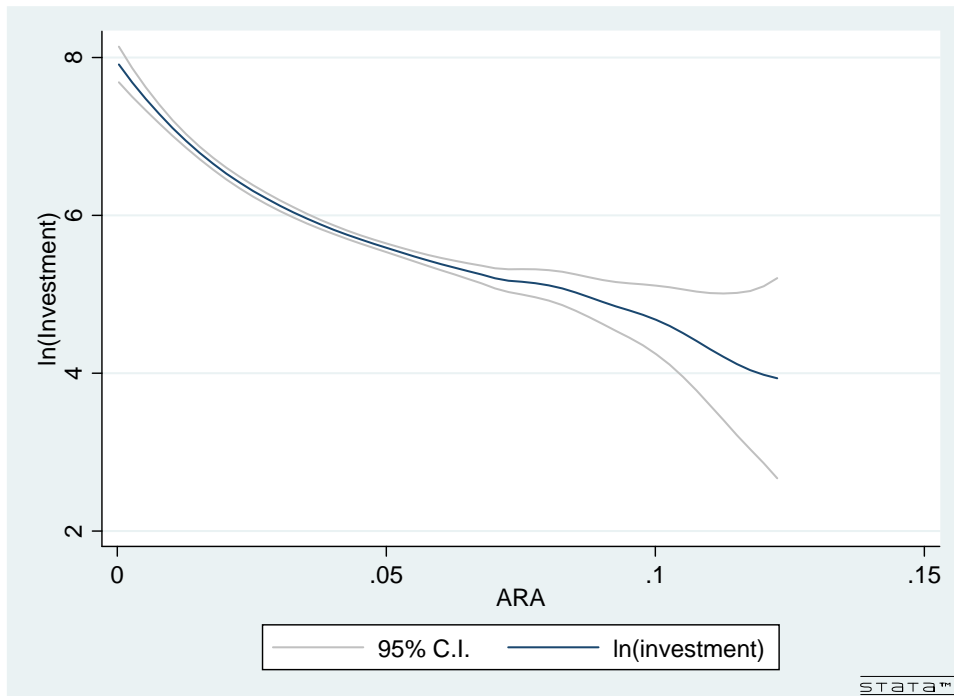
(a) ARA and Wealth



(b) Income-Based RRA and Wealth

Subsample: home-owners. The vertical axis plots a weighted local second degree polynomial smoothing of the risk aversion measure. The observations are weighted using an Epanechnikov kernel with a bandwidth of 0.75. The horizontal axis measures the (log) net worth and the (log) median house price at the investor's zip code at the time of the portfolio choice, our two proxies for investor wealth.

Figure 6: Risk Aversion and Wealth in the Cross Section



The vertical axis plots a weighted local second degree polynomial smoothing of the overall amount invested in LC (in log). The observations are weighted using an Epanechnikov kernel with a bandwidth of 0.75. The horizontal axis measures ARA estimated with specification (13).

Figure 7: Absolute Risk Aversion and Overall Investment in LC

Variable	Mean	Std. Dev.	Median
A. Borrower Characteristics			
FICO score	694.3	38.2	688.0
Debt to Income	0.128	0.076	0.128
Monthly Income (\$)	5,427.6	5,963.1	4,250.0
Amount borrowed (\$)	9,223.7	6,038.0	8,000.0
B. Investor Characteristics			
Male	83%		100%
Age	43.4	15.0	40.0
Married	56%		100%
Home Owner	75%		100%
Net Worth, Imputed (\$1,000)	663.0	994.4	375.0
Median House Value in Zip Code (\$1,000)	397.6	288.0	309.6
% Change in House Price, 10-2007 to 04-2008	-4.0%	5.8%	-3.6%

Sources: Lending Club, Acxiom, and Zillow. October 2007 to April 2008. FICO scores and debt to income ratios are recovered from each borrower’s credit report. Monthly incomes are self reported during the loan application process. Amount borrowed is the final amount obtained through Lending Club. Lending Club obtains investor demographics and net worth data through a third party marketing firm (Acxiom). Acxiom uses a proprietary algorithm to recover gender from the investor’s name, and matches investor names, home addresses, and credit history details to available public records to recover age, marital status, home ownership status, and net worth. We use investor zip codes to match the LC data with real estate price data from the Zillow Home Value Index. The Zillow Index for a given geographical area is the median property value in that area.

Table 1: Borrower and Investor Characteristics

Sample/Subsample:	All Investments			Diversified investments			With real estate data		
	(1)			(2)			(3)		
	Mean	S.D	Median	Mean	S.D	Median	Mean	S.D	Median
A. Unit of observation: investor-bucket-month									
	(N = 50,254)			(N = 43,662)			(N = 37,248)		
Investment (\$)	302.8	2,251.4	50.0	86.0	206.9	50.0	90.1	220.5	50.0
N Projects in Bucket	1.9	1.8	1.0	2.0	1.8	1.0	2.0	1.8	1.0
Interest Rate	12.89%	2.98%	12.92%	12.91%	2.96%	12.92%	12.92%	2.97%	12.92%
Default Rate	2.77%	1.45%	2.69%	2.78%	1.45%	2.84%	2.79%	1.45%	2.84%
E(PV \$1 investment)	1.122	0.027	1.122	1.122	0.027	1.123	1.122	0.027	1.123
Var(PV \$1 investment)	0.036	0.020	0.035	0.027	0.020	0.022	0.036	0.020	0.035
B. Unit of observation: investor-month									
	(N = 5,191)			(N = 3,745)			(N = 3,145)		
Investment	2,932	28,402	375	1,003	2,736	375	1,067	2,934	400
N Buckets	9.7	8.7	7.0	11.7	8.4	10.0	11.8	8.5	10.0
N Projects	18.8	28.0	8.0	23.3	28.9	14.0	23.8	29.5	14.0
E(PV \$1 investment)	1.121	0.023	1.121	1.121	0.021	1.121	1.121	0.021	1.121
Var(PV \$1 investment)	0.0122	0.0159	0.0054	0.0052	0.0065	0.0025	0.0066	0.0070	0.0038

Each observation in panel A represents an investment allocation, with at least 2 risk buckets, by investor i in risk bucket z in month t . In panel B, each observation represents a portfolio choice by investor i in month t . An investment constitutes a dollar amount allocation to projects (requested loans), classified in 35 risk buckets, within a calendar month. Loan requests are assigned to risk buckets according to the amount of the loan, the FICO score, and other borrower characteristics. Lending Club assigns and reports the interest rate and default probability for all projects in a bucket. The expectation and variance of the present value of \$1 investment in a risk bucket is calculated assuming a geometric distribution for the idiosyncratic monthly survival probability of the individual loans and independence across loans within a bucket. The sample in column 2 excludes portfolio choices in a single bucket and non-diversified investments. The sample in column 3 also excludes portfolio choices made by investors located in zip codes that are not covered by the Zillow Index.

Table 2: Descriptive Statistics

	ARA	θ	Expected Income	Income Based RRA
Mean	0.03679	1.086	130.1	2.85
sd	0.02460	0.027	344.3	3.62
p1	-0.00837	1.045	4.11	-0.16
p10	0.01126	1.059	8.08	0.28
p25	0.02271	1.075	16.0	0.56
p50	0.04395	1.086	45.9	1.62
p75	0.04812	1.094	111.1	3.66
p90	0.05293	1.105	297.1	7.29
p99	0.08562	1.157	1,255.1	17.18
N	3,145	3,145	3,145	3,145

Absolute Risk Aversion (ARA) and intercept θ obtained through the OLS estimation of the following relationship for each investment:

$$E[R_z] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \cdot \sigma_z^2 + \xi_z^i$$

where the left (right) hand side variable is expected return (idiosyncratic variance times the investment amount) of the investment in bucket z. The income based Relative Risk Aversion (RRA) is the estimated ARA times the total expected income from the investment in Lending Club. pN represents the N^{th} percentile of the distribution.

Table 3: Unconditional distribution of estimated risk aversion parameters

	ARA	θ	Expected Income	Income Based RRA
2007m10	0.028 (0.020)	1.057 (0.014)	173.3 (608.5)	1.229 (0.980)
2007m11	0.032 (0.018)	1.065 (0.013)	111.3 (337.6)	1.195 (0.952)
2007m12	0.037 (0.016)	1.066 (0.013)	78.5 (199.8)	1.446 (1.527)
2008m1	0.036 (0.031)	1.083 (0.040)	175.9 (522.8)	2.774 (3.676)
2008m2	0.040 (0.022)	1.089 (0.018)	123.3 (305.9)	3.179 (3.906)
2008m3	0.037 (0.025)	1.097 (0.023)	146.4 (288.0)	3.841 (4.302)
2008m4	0.039 (0.026)	1.089 (0.023)	63.9 (109.8)	2.011 (2.275)

Absolute Risk Aversion (ARA) and intercept θ obtained through the OLS estimation of the following relationship for each investment:

$$E[R_z] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \cdot \sigma_z^2 + \xi_z^i$$

where the left (right) hand side variable is expected return (idiosyncratic variance times the investment amount) of the investment in bucket z. The income based Relative Risk Aversion (RRA) is the estimated ARA times the total expected income from the investment in Lending Club. Standard deviations in parenthesis.

Table 4: Mean risk aversion and systematic risk premium by month

ARA			θ		
Automatic (1)	Non-Automatic (2)	Δ (3)	Automatic (4)	Non-Automatic (5)	Δ (6)
A. Full Sample (n = 227)					
0.0368 (0.0215)	0.0356 (0.0194)	-0.0012 (0.0204)	1.079 (0.0209)	1.080 (0.0226)	0.001 (0.0213)
B. Subsample: October-December 2007 (n = 74)					
0.0355 (0.0235)	0.0340 (0.0192)	-0.0016 (0.0223)	1.062 (0.0132)	1.063 (0.0193)	0.001 (0.0168)
C. Subsample: January-April 2008 (n = 153)					
0.0374 (0.0206)	0.0364 (0.0195)	-0.0011 (0.0195)	1.087 (0.0188)	1.089 (0.0190)	0.002 (0.0232)

Descriptive statistics of the Absolute Risk Aversion (ARA) and θ obtained as in Table 3, over the subsample of investments where the estimates can be obtained separately using Automatic (buckets suggested by optimization tool) and Non-Automatic (buckets chosen directly by investor) bucket choices for the same investment. The mean and standard deviation (in parenthesis) of both estimates and the difference for the same investment are shown for the full sample and for 2007 and 2008 separately. The mean differences are not significantly different from zero in any of the samples.

Table 5: Estimates from Automatic and Non-Automatic Buckets

Dependent Variable: (in logs)	ARA (1)	Income based RRA (2)	Investment (3)	First Stage log (Net Worth) (4)
A. OLS				
log (Net Worth)	-0.009** (0.004)	0.022*** (0.008)	0.035*** (0.009)	
R-squared	0.003	0.005	0.010	
Observations (investors)	1,514	1,514	1,514	
B. Errors-in-Variables (Instrument: House Value)				
log (Net Worth)	-0.059*** (0.019)	0.123*** (0.031)	0.203*** (0.038)	
log (House Value)				1.664*** (0.146)
Observations (investors)	1,261	1,261	1,261	1,261

Estimated elasticity of risk aversion to wealth in the cross section. Panel A presents the OLS estimation of the *between* model and Panel B presents the errors-in-variables estimation using the median house value in the investor's zip code as an instrument for net worth. The dependent variables are the (log) absolute risk aversion (column 1), income-based relative risk aversion (column 2), and investment amount in LC (column 3), averaged for each investor i across all portfolio choices in our sample. The right hand side variable is the investor (log) net worth (from Acxiom). Column 4 reports the first stage of the instrumental variable regression: the dependent variable is (log) net worth and the right hand side variable is the average (log) median house price in the investor's zip code (from Zillow). Standard errors are heteroskedasticity robust and clustered at the zip code level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Table 6: Risk Aversion and Wealth, Cross Section Estimates

Dependent Variable: (in logs)	ARA (1)	Income based RRA (2)	Investment (3)
A. No Fixed Effects			
log (House Value)	-0.166*** (0.047)	0.192*** (0.048)	0.367*** (0.070)
Risk Premium Controls	Yes	Yes	Yes
Investor Fixed Effects	No	No	No
R-squared	0.020	0.010	0.032
Observations	2,030	2,030	2,030
Investors	1,292	1,292	1,292
B. Investor Fixed Effects			
log (House Value)	-2.825* (1.521)	-4.815*** (1.611)	1.290 (1.745)
Risk Premium Controls	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes
R-squared (adj)	0.008	0.011	0.001
Observations	2,030	2,030	2,030
Investors	1,292	1,292	1,292

Estimated investor-specific elasticity of risk aversion to wealth. The left hand side variables are the (log) absolute risk aversion (column 1), income-based relative risk aversion (column 2), and investment amount in LC (column 3), obtained for investor i for a portfolio choice in month t . The right hand side variables are the (log) median house price in the investor's zip code in time t , and an investor fixed effect (omitted). Standard errors are heteroskedasticity robust and clustered at the zip code level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Table 7: Risk Aversion and Wealth Shocks, Investor-Specific Estimates

Appendix: Alternative Utility Frameworks

A.1 Preferences over Income and Wealth

Consider the following preferences over, both, wealth and income of specific components of the investor's portfolio (narrow framing):

$$U(\{y_k\}_{k=1}^K, W) = \sum_{k=1}^K u(y_k, W)$$

where $k = 1, \dots, K$ corresponds to the different sub-portfolios over which the investor exhibits local preferences. Income from each sub-portfolio k is given by the investment amount and its return, $y_k = I_k R_k$. W is the investor's overall wealth, and the amount invested in each portfolio satisfies $\sum_{k=1}^K I_k = W$.

The LC sub-portfolio is denoted $k = L$, with income given by the return over the 35 risky buckets $y_L = I_L \sum_{z=1}^{35} x_z R_z$. The first order condition that characterizes the a positive position in bucket z within LC is:

$$foc(x_z) : E[u_y(y_L, W) I_L R_z] - \mu_L = 0$$

where u_y corresponds to the partial derivative of the utility function with respect to the income generated by the sub-portfolio L , y_L , and μ_L is the multiplier over the constraint $\sum_{z=1}^{35} x_z = 1$. The linearization of this expression around expected income $E[y_L]$ is equivalent to expression (9):

$$E[R_z] = \theta_L + ARA_L \cdot I_L x_z \cdot var[r_z] \tag{A.1}$$

$I_L x_z$ is the total amount invested in bucket z , equivalent to $W x_z$ in the body of the paper. Under Assumption (1), the investor specific parameter θ_L is defined as follows:

$$\theta_L \equiv \frac{\mu_L}{u_y(y_L, W)} + ARA_L \cdot I_L \cdot \beta_L^2 var[R_m]$$

This parameter is constant across risk buckets $z = 1, \dots, 35$ and is recovered, as in the body of the paper, with an investment-specific fixed effect. The absolute risk aversion ARA_L estimated with equation (A.1) describes the investor's preferences over fluctuations in income from the LC portfolio; it is defined as follows:

$$ARA_L \equiv -\frac{u_{yy}(y_L, W)}{u_y(y_L, W)}$$

The goal of the paper is to characterize how the curvature of the utility function changes with wealth. The results in Subsection (6.3) suggest that the local curvature of the utility function decreases with wealth. In the context of this behavioral framework, this implies that for $k = 1, \dots, K$:

$$\frac{\partial ARA_k}{\partial W} < 0$$

This behavioral model can also reconcile high risk aversion estimates in low stake environments

and lower risk aversion when the lottery involves larger amounts, which requires the following:

$$\frac{\partial ARA_k}{\partial y_k} < 0$$

Consider, for example, the case of constant relative risk aversion over income:

$U = E \left[\sum_{k=1}^K [1 - \rho(W)]^{-1} y_k^{1-\rho(W)} \right]$, with $\rho'(W) < 0$. The absolute risk aversion is given by $ARA_k = \frac{\rho(W)}{y_k}$, which is lower for larger stakes, y_k . And, for any portfolio component $k = 1, \dots, K$, the curvature of the preference function decreases with overall wealth, W . With these preferences, the income-based Relative Risk Aversion, typically computed in the experimental literature and also estimated in this paper, is constant across sub-portfolios, $ARA_k y_k = \rho(W)$, and decreases with wealth.

This behavioral model, in which utility depends (in a non-separable way) on, both, the overall wealth level and the flow of income from specific components of the agent's portfolio, is in line with Barberis and Huang (2001) and Barberis et al. (2006), which propose a framework where agents exhibit loss aversion over changes in specific components of their overall portfolio, together with decreasing relative risk aversion over their entire wealth, consistent with the findings of this paper. In the expected utility framework, Cox and Sadiraj (2006) propose a utility function with two arguments (income and wealth) where risk aversion is defined over changes in income but it is sensitive to the overall wealth level.

A.2 Loss Aversion over Changes in Overall Wealth

Consider the following preferences, which exhibit loss aversion with coefficient $\alpha \geq 1$ around a benchmark consumption \bar{c}

$$U = \alpha \cdot E [u(c)|c < \bar{c}] \cdot Pr [c < \bar{c}] + E [u(c)|c > \bar{c}] \cdot Pr [c > \bar{c}]$$

Since LC is a negligible part of the investor's wealth and the return is bounded between default and full repayment of all loans in the portfolio (see Table 2), the distribution of consumption is virtually unaffected by the realization of the independent component of bucket z . Then, we define $\omega \equiv c - W x_z r_z$, which is independent from r_z , and approximate the distribution of c with the distribution of ω : $F(c) \approx F(\omega)$. Under this approximation, a marginal increase in x_z does not affect the distribution $F(\omega)$ and the first order condition that characterizes the investor's portfolio choice is:

$$foc(x_z) : \alpha \cdot E [u'(c)(r_z - 1)|\omega < \bar{c}] \cdot Pr [\omega < \bar{c}] + E [u'(c)(r_z - 1)|\omega > \bar{c}] \cdot Pr [\omega > \bar{c}] = 0$$

Since ω and r_z are independently distributed, a first order linearization of expected marginal utility is given by:

$$\begin{aligned} E [u'(c)r_z|\omega < \bar{c}] &= u'(E[c|\omega < \bar{c}])E[r_z] + u''(E[c|\omega < \bar{c}])E[(\omega - E[\omega] + r_z - E[r_z])r_z|\omega < \bar{c}] \\ &= u'(E[c|\omega < \bar{c}])E[r_z] + u''(E[c|\omega < \bar{c}])var[r_z] \end{aligned}$$

Replacing, the first order condition is approximated by:

$$E[R_z] = \theta + \widetilde{ARA} \cdot W x_z \cdot var[r_z]$$

This condition is equivalent to the one in the body of the paper, irrespectively of the value of \bar{c} or the existence of multiple *kinks*. However, the absolute risk aversion estimated using this equation is not the one evaluated around expected consumption, as in the body of the paper. Instead, it is a weighted average of the absolute risk aversions evaluated in the intervals defined by the loss aversion *kinks*:

$$\widetilde{ARA} \equiv \lambda \cdot ARA^- + (1 - \lambda) \cdot ARA^+$$

$$\begin{aligned} \text{where :} \quad \lambda &\equiv \frac{\alpha F[\bar{c}]}{\alpha F[\bar{c}] + (1 - F[\bar{c}])} \\ ARA^- &\equiv -\frac{u''(E[c|c < \bar{c}])}{u'(E[c|c < \bar{c}])} \\ ARA^+ &\equiv -\frac{u''(E[c|c > \bar{c}])}{u'(E[c|c > \bar{c}])} \end{aligned}$$

Still, as in the body of the paper, the optimal investment in a risk bucket z is not explained by first order risk aversion; it is given by its expected return and second order risk aversion over the volatility of its idiosyncratic component.

Moreover, the wealth elasticity of risk aversion computed in the paper also characterizes the sensitivity of the preference curvature to wealth. The interpretation is, however, slightly different. From the definition of \widetilde{ARA} , we can derive the following expression for its wealth elasticity:

$$\xi_{\widetilde{ARA},W} = \tilde{\lambda} \cdot \xi_{ARA^-,W}^- + (1 - \tilde{\lambda}) \cdot \xi_{ARA^+,W}^+ + \alpha \frac{\partial F[\bar{c}]}{\partial W} \left(\frac{ARA^- - ARA^+}{\widetilde{ARA}} \right) \quad (\text{A.2})$$

where $\xi_{ARA^-,W}^-$ and $\xi_{ARA^+,W}^+$ correspond to the wealth elasticities of ARA^- and ARA^+ , respectively, and $\tilde{\lambda} \equiv \lambda ARA^- / \widetilde{ARA}$. Intuitively, the wealth elasticity of \widetilde{ARA} is a weighted average of the wealth elasticities of risk aversion below and above the *kink*, and accounts for the change in the probability of incurring in losses after the change in wealth (i.e., $\partial F[\bar{c}]/\partial W < 0$).³⁷

³⁷Our finding that $\xi_{\widetilde{ARA},W} < 0$ requires $\xi_{ARA,W} < 0$ as well. By contradiction, if $\xi_{ARA,W} > 0$, then $ARA^- - ARA^+ < 0$, which would result in the right hand side of expression (A.2) to be positive.

B On Line Appendix

B.1 Optimization Tool

Those investors who follow the recommendation of the optimization tool make a sequential portfolio decision. First, they decide how much to invest in the entire LC portfolio. And second, they choose the desired level idiosyncratic risk in the LC investment, from which the optimization tool suggests a portfolio of loans.

The first decision, how much to invest in LC, follows the optimal portfolio choice model in Section 3, where the security $z = L$ refer to the LC overall portfolio. The optimal investment in LC is therefore given by equation (8):

$$E[r_L] - 1 = ARA^i \cdot W^i x_L^i \cdot var[r_L] \quad (\text{B.1})$$

$(E[r_L] - 1) / var[r_L]$ corresponds to the investor's preferred risk-return ratio of the her LC portfolio. Although this ratio is not directly observable, we can infer it from the *Automatic* portfolio suggested by the optimization tool.

The optimization tool suggests the minimum variance portfolio given the investor's choice of idiosyncratic risk exposure. The investor marks her preferences by selecting a point in the $[0, 1]$ interval: 0 implies fully diversified idiosyncratic risk (typically only loans from the A1 risk bucket) and 1 is the (normalized) maximum idiosyncratic risk. Figure 1 provides two snapshots of the screen that the lenders see when they make their choice.

For each point on the $[0, 1]$ interval, the website generates the efficient portfolio of risk buckets. The loan composition at the interior of each risk bucket exhausts the diversification opportunities, with the constraint that an investment in a given loan cannot be less than \$25.

The proposed share in each risk bucket $s_z \geq 0$ for $z = 1, \dots, 35$ satisfies the following program:

$$\min_{\{s_z\}_{z=1}^{35}} \sum_{z=1}^{35} s_z^2 var[r_z] - \lambda_0 \left\{ \sum_{z=1}^{35} s_z E[R_z] - E[R_L] \right\} - \lambda_1 \left\{ \sum_{z=1}^{35} s_z - 1 \right\}$$

$var[r_z]$ and $E[R_z]$ are the idiosyncratic variance and expected return of the (optimally diversified) risk bucket z , computed in equations (1) and (2); and $E[R_L]$ is the demanded expected return of the entire portfolio.

Although the optimization tool operates under the assumption that LC has no systemic component, i.e., $\beta_L = 0$, the suggested portfolio also minimizes variance for a given overall expected independent return, $E[r_L]$. That is, the problem is not affected by subtracting a common systematic component, $\beta_L E[R_m]$ on both sides of the expectation constraint. The resulting efficient portfolio suggested by the website satisfies the following condition for every bucket z for which $s_z > 0$:

$$s_z = \lambda_0^i \frac{E[r_z] - \lambda_1^i}{var[r_z]} \quad (\text{B.2})$$

That is, the share of LC investment allocated in bucket z is proportional to the bucket's mean variance ratio. And the proportionality factor, λ_0^i , represents the risk preferences of the investor,

imbedded in her chosen point on the $[0, 1]$ interval:

$$\lambda_0^i = \frac{\text{var}[r_L]}{E[r_L] - \lambda_1^i} \quad (\text{B.3})$$

It is possible to recover, from the Automatic portfolio composition, the investor's preferred risk-return ratio. Combining equations (B.2) and (B.3) with the optimal LC investment condition (B.1), we obtain the following expression:

$$E[R_z] = (\beta_L E[R_m] + \lambda_1^i) + ARA^i \cdot W^i x_L^i s_z^i \cdot \text{var}[r_z] \frac{(E[r_L] - \lambda_1^i)}{(E[r_L] - 1)} \quad (\text{B.4})$$

Note that $W^i x_L^i s_z^i$ is the total amount invested in bucket z , which is equivalent to $W^i x_z^i$ in Section 3.

Our estimates from the specification (13) may be biased by the inclusion of the *Automatic* choices. The magnitude of the bias is:

$$\text{bias}^i = \frac{E[R_L] - \theta_A^i}{E[R_L] - \theta_N^i} - 1.$$

where θ_N^i and θ_A^i correspond to the investor specific θ constant in the specification equation (9) for non-automatic and automatic choices respectively:

$$\begin{aligned} \theta_A^i &\equiv \lambda_1^i + \beta_L E[R_m] \\ \theta_N^i &\equiv 1 + \beta_L E[R_m] \end{aligned}$$

We find that the intercepts estimated from *Automatic* and *Non-Automatic* choices (θ_A and θ_N) are equal (see Table 5). We therefore conclude that including *Automatic* choices does not bias our results.

B.2 Investment Amount

Limiting, for simplicity, the investor's outside options to the risk free asset and the market portfolio, the problem of investor i is:

$$\max_x Eu(W^i (x_f^i + x_m^i R_m + x_L^i R_L))$$

where R_L is the overall return of the efficient LC portfolio. The efficient LC portfolio composition is constructed renormalizing the optimal shares in equation (9): $R_L = \sum_{z=1}^{Z_L} \tilde{x}_z R_z$ where $\tilde{x}_z \equiv x_z / \sum_{z=1}^{35} x_z$. A projection of the return R_L against the market, parallel to equation (4), gives the investor's market sensitivity, β_L^i , and independent return:

$$R_L = \beta_L^i \cdot R_m + r_L$$

The investor's budget constraint can be rewritten as $c^i = W^i (x_f^i + \tilde{x}_m^i R_m + x_L^i r_L)$, where $\tilde{x}_m^i = x_m^i + x_L^i \beta_L^i$ incorporates the market risk imbedded in the LC portfolio.

A linearization of the first order condition around expected consumption results in the following

optimality condition:

$$E[R_L] = \theta^i + ARA^i \cdot I_L^i \cdot \text{var}[r_L]$$

where I_L^i is the total investment in LC, $I_L^i = x_L^i W^i$. The composition of the LC portfolio is optimal; then, differentiating the expression above with respect to outside wealth and applying the envelope condition, we derive the following result:

$$\begin{aligned} d \ln(ARA) &= -d \ln(I_L) \\ d \ln(RRA) &= -d \ln\left(\frac{I_L}{W}\right) \end{aligned}$$

ARA and RRA refer to absolute and wealth-based relative risk aversion: $ARA \equiv -\frac{u''(E[c^i])}{u'(E[c^i])}$ and $RRA \equiv -\frac{u''(E[c^i])}{u'(E[c^i])} W$. We obtain the following testable implications, which are tested in Subsection 7.2:

Result 1. *In the cross section of investors, the elasticity between the investor-specific ARA and the amount invested in LC, I_L , is -1 .*

Result 2. *If the absolute risk aversion, ARA , decreases (increases) in outside wealth, then the amount invested in LC, I_L , increases (decreases) in outside wealth.*

Result 3. *If the wealth-based RRA decreases (increases) in outside wealth, then the share of wealth invested in LC, I_L/W , increases (decreases) in outside wealth.*

B.3 Alternative Formulation of the Portfolio Choice

The optimality condition in Treynor and Black (1973) is not different from the one derived from the classic portfolio choice problem, provided that the comovement between asset returns satisfies Assumption 1. Consider the following portfolio choice problem

$$\begin{aligned} \max_{x_0, \{x_z\}_{z=1}^Z} & Eu \left(W^i \left[x_0^i R_0^i + \sum_{z=1}^Z x_z^i R_z^i \right] \right) \\ \text{s.t.} & x_0 + \sum_{z=1}^Z x_z = 1 \\ & x_z = 0 \text{ or } x_z \geq 25 \text{ for all } z. \end{aligned}$$

The shares $\{x_z\}_{z=1}^{Z=35}$ correspond to the LC risk buckets and x_0 refers to all investments outside LC.

The first order condition characterizing the optimal portfolio share of any bucket h is:

$$foc(x_h) : u'(c_i) \cdot W^i \cdot E[R_h] - \mu^i - \lambda_h^i (x_h > 25) = 0$$

where μ^i corresponds to the multiplier on the budget constraint, $x_0 + \sum_z x_z = 1$, and λ_h^i is the Khun-Tucker multiplier on the minimum investment constraint, which is zero for all those buckets for which the investor has a positive position.

A first-order linearization on the first order condition around expected consumption results in the following optimality condition for all buckets with positive investment:

$$foc(x_h) : E [u' (E[c^i]) W^i R_h^i] + u''(E[c^i])(W^i)^2 \left(x_0^i cov [R_0^i, R_h^i] + \sum_{z=1}^Z x_z^i cov [R_z^i, R_h^i] \right) - \mu^i = 0$$

Under assumption 1, the covariances between any two LC bucket returns and between any LC bucket and outside wealth are constant. In particular, given that their comovement is given by a common macroeconomic factor (i.e., the market return), they can be expressed as follows:

$$\begin{aligned} \forall z & : cov[R_z^i, R_0^i] = \beta_L^i \beta_0^i var[R_m] \\ \forall z \neq h & : cov[R_z^i, R_h^i] = (\beta_L^i)^2 var[R_m] \\ \forall z & : cov[R_z^i, R_z^i] = (\beta_L^i)^2 var[R_m] + var[r_z^i] \end{aligned}$$

where β_L^i is the market sensitivity, or *beta*, of the LC returns, defined in equation (4) and assumed constant across buckets; and β_0^i is the corresponding sensitivity for the investor's outside wealth. The variance of any risk bucket z is given by its systematic component, $(\beta_L^i)^2 var[R_m]$, and its idiosyncratic risk, derived in equation 1: $var[r_z^i] = \sigma_z^2/n_z^i$.

Rearranging terms, we derive the same expression as in (9):

$$E[R_h] = \theta^i + ARA^i \cdot \frac{W^i x_h^i}{n_h^i} \cdot \sigma_h^2$$

where ARA^i is the absolute risk aversion of the investor, and θ^i is an investor fixed effect that recovers the budget constraint multiplier and her marginal exposure to systematic risk, common across buckets:

$$\theta^i \equiv \frac{\mu^i}{W^i u'(E[c^i])} + ARA^i W^i \beta_L^i var[R_m] \left(\beta_0^i x_0^i + \beta_L^i \sum_{z=1}^Z x_z^i \right)$$

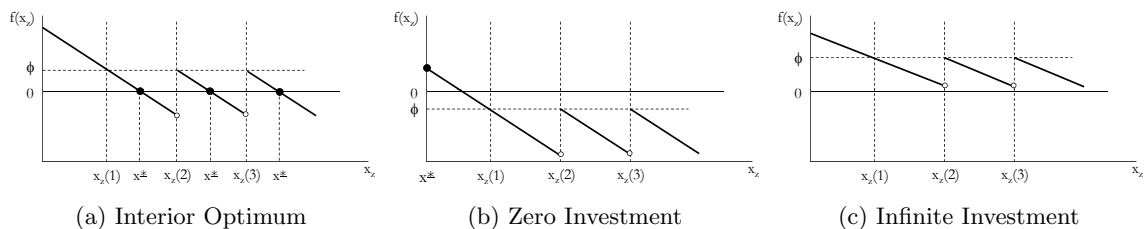
B.4 The 25\$ Minimum per Loan Constraint

The first order condition (linearized) in equation (8) is satisfied with equality for the local interior optimum x_z^i , given the agent's wealth W^i and absolute risk aversion ARA^i :

$$f(x_z) : E[R_z] - \theta^i - ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \cdot \sigma_z^2$$

LC imposes a restriction of \$25 for the minimum amount of dollars in each loan. Then, the optimal (i.e., maximum) number of loans within the bucket is $n_z^i = int(W^i x_z^i / 25)$. The first order condition above decreases monotonically on x_z for a constant n_z , but it presents discontinuities around those share values that trigger an increase the number of loans —i.e., $x_z^i(n) = (25n)/W^i$ for any integer number of loans n . In addition, the function $f(x)$ takes the same value when evaluated at the trigger share values: $\forall n, f(x_z^i(n)) = \phi^i$.

The figures above show the three potential optimality conditions that satisfy the first order



condition above, taking into consideration the \$25 minimum restriction: (a) the interior solution, in which the agent invests a positive amount; (b) the corner solution in which the minimum investment constraint binds and the bucket is not chosen to be part of the portfolio, and (c) the case in which the optimal investment is infinite. The interior solution, on which our empirical specification is based, is attained when $\phi \geq 0$ and $\lim_{x \rightarrow x_z(n)^-} f(x) < 0$ (Figure (a)). In this case, the optimal investment is positive and $f(x)$ is equal to zero. Notice that there are multiple local optima in this case. When $\phi < 0$, the interior optimum requires $x < 25$ and the minimum per loan constraint binds. The investor does not allocate any funds to the bucket in this case (Figure (b)). Subsection 7.1 uses this condition for chosen and foregone buckets to test the consistency of investors' preferences. Finally, Figure (c) shows the scenario in which $\lim_{x \rightarrow x_z(n)^-} f(x) > 0$: for any x_z , the marginal increase in expected utility that results from adding an extra dollar to the bucket z is larger than the corresponding increase in risk. The optimal investment in the bucket z is therefore infinite. No LC investment in our sample corresponds to this case.