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RISK AVERSION AND WEALTH:
EVIDENCE FROM PERSON-TO-PERSON LENDING PORTFOLIOS

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ABSTRACT

We estimate risk aversion from the actual financial decisions of 2,168 investors in Lending Club (LC), a person-to-person lending platform. We develop a methodology that allows us to estimate risk aversion parameters from each portfolio choice. Since the same individual makes repeated investments, we are able to construct a panel of risk aversion parameters that we use to disentangle heterogeneity in attitudes towards risk from the shape of the utility function. In the cross section, we find that wealthier investors are more risk averse. Using changes in house prices as a source of variation, we find that investors become more risk averse after a negative wealth shock. These preferences consistently extrapolate to other investor decisions within LC.

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1 Introduction

The relationship between risk aversion and wealth has long been a central concern in finance and macroeconomics. Theoretical predictions on investment, asset prices, and the cost of business cycles, depend crucially on assumptions about the curvature of the utility function and its heterogeneity across agents.[1] Despite its importance, there is limited direct empirical evidence on the elasticity of risk aversion to wealth. Most is based on cross sectional data, which requires assuming that heterogeneous attitudes towards risk across agents with different wealth arise from the *same* preference function. If agents have heterogeneous preferences, however, cross sectional analysis will lead to incorrect inferences about the shape of the utility function when wealth and preferences are correlated. Such a correlation may arise, for example, if agents with heterogenous propensity to take risk make different investment choices, which in turn affect their wealth. Alternatively, an unobserved investor characteristic, such as having more educated parents, may jointly affect wealth and the propensity to take risk. To, both, characterize the properties of the joint distribution of preferences and wealth in the cross section, and estimate the parameters describing the shape of the utility function, one needs to observe also how the risk aversion of the same individual changes with wealth shocks (see Chiappori and Paiella (2008)).

This paper exploits a novel environment to estimate both relationships. We analyze the risk taking behavior of 2,168 investors based on their actual financial decisions in Lending Club (LC), a person-to-person lending platform that allows individuals to invest in diversified portfolios of small loans. We develop a methodology that allows us to estimate risk aversion parameters from each portfolio choice. Since the same individual makes repeated investments, we are able to construct a panel of risk aversion parameters that we use to disentangle heterogeneity in attitudes towards risk from the shape of the utility function.

[1] See Kocherlakota (1996) for a discussion of the literature aiming at resolving the *equity premium* and *low risk free rate* puzzles under different preference assumptions. Campbell and Cochrane (1999), for example, model preferences with *habit formation* that produce cyclical variations in risk aversion, and decreasing relative risk aversion after a positive wealth shock. Gollier (2001) shows that wealth inequality raises the equity premium if the absolute risk aversion is concave in wealth. Schulhofer-Wohl (2008) proposes a model with heterogenous risk aversion to evaluate the welfare cost of real business cycles.

Our estimation method is derived from an optimal portfolio model where investors not only hold the market portfolio, but also securities for which they have subjective *insights* (Treynor and Black (1973)). We treat investments in LC as special-insight securities, with returns that are correlated with with other securities through a common systematic factor (Sharpe's Diagonal Model). This implies that LC returns can be decomposed into a systematic component, i.e., correlated with macroeconomic fluctuations, and a pure idiosyncratic component. We use the idiosyncratic component to characterize investors' preferences: an investor's Absolute Risk Aversion (ARA) is given by the additional expected return that makes her indifferent about allocating the marginal dollar in a loan with higher idiosyncratic default probability.

This modeling approach has two main advantages. First, estimating risk preferences from the idiosyncratic component of returns implies that the estimates are independent from the investors' overall risk exposure or wealth. Thus, our approach avoids the difficulties faced when estimating risk aversion from the share of risky and riskless assets in the investors' portfolio, which requires knowing the amount and risk characteristics of unobservable wealth. Second, by measuring the curvature of the utility function directly from the first order condition of the portfolio choice problem, we do not need to impose a specific shape of the utility function. This implies, also, that our method obtains consistent estimates for the curvature of the utility function, both, under the expected utility framework and common alternative specifications (i.e., loss aversion, narrow framing).

The average ARA implied by the portfolio choices in our sample is 0.037. Our estimates imply an average income-based Relative Risk Aversion (income-based RRA), a commonly reported risk preference parameter obtained assuming that the investor's outside wealth is zero, of 2.85, with substantial unexplained heterogeneity and skewness.[2] The level, distribution, and skewness of the risk aversion parameters are similar to those obtained in laboratory and field experiments.[3] The similarity indicates that investors in our sample, despite being a self selected sample of

[2]The income-based RRA, often reported in the experimental literature, is defined as $ARA \cdot E[I]$, where $E[I]$ is the expected income from the lottery offered in the experiment.

[3]See for example Barsky, Juster, Kimball and Shapiro (1997), Holt and Laury (2002), Choi, Fisman, Gale and Kariv (2007), and Harrison, Lau and Rutstrom (2007b).

individuals that invest on-line, have similar risk preferences to those in experimental studies.

The comparison to designed experiments is relevant because investors in our model face choices that are similar 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). Thus, our results provide an external validation in a real life investment environment to the estimates obtained from laboratory experiments.[4]

The key identification assumption is that investors believe that all LC investments have a common systematic risk—i.e., that their returns have the same covariance with the market. To test this assumption, we compare risk aversion parameters estimated from investments done through two alternative portfolio choice methods: manually or through an optimization tool. When an investor chooses manually, she selects loans by processing herself the information on interest and default rates provided on LC's website. When an investor uses the tool, the tool processes this information by providing all the possible efficient (minimum variance) portfolios that can be constructed with the available loans. The investor then selects among the efficient portfolios the preferred one according to her own risk preferences. Importantly, the tool uses the same modeling assumptions regarding investors' beliefs that we use in our framework. We find that investors exhibit the same risk preferences when choosing portfolios manually or through the tool. This implies that investors' beliefs about the risk and return of LC investments are consistent with our identification assumptions.

We use the estimated parameters to explore the relationship between risk preferences and wealth. Using imputed net worth as of October 2007 as a proxy for wealth in the cross section of investors, we find that wealthier investors exhibit lower ARA and higher RRA when choosing

[4]For estimation of risk aversion in real life environments, see also Jullien and Salanie (2000), Jullien and Salanie (2008), Bombardini and Trebbi (2007), Cohen and Einav (2007), Harrison, Lau and Towe (2007a), Chiappori, Gandhi, Salanie and Salanie (2008), Post, van den Assem, Baltussen and Thaler (2008), Chiappori, Gandhi, Salanie and Salanie (2009), and Barseghyan, Prince and Teitelbaum (2010).

LC loan portfolios.[5] Our preferred specification, which corrects for measurement error in our wealth proxy, obtains an elasticity of ARA to wealth of -0.059. This implies a cross sectional wealth elasticity of RRA of 0.94. We then use the decline in house prices during our sample period—October 2007 to April 2008–as a source of variation to estimate the elasticity of investor-specific risk aversion to changes in wealth. Investors become more risk averse after experiencing a negative wealth shock, indicating that investors' utility function exhibits decreasing relative risk aversion. The contrasting signs of the cross sectional and investor-specific wealth elasticities indicate that there is a strong positive correlation between risk aversion and wealth in the cross section.

Our results highlight that 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. To distinguish them, we exploit the panel structure of our risk aversion estimates and the plausible exogenous variation in wealth. Tanaka, Camerer and Nguyen (2010) also recognize this empirical challenge, and use rainfall across villages in Vietnam as an instrument for wealth. However, due to the cross sectional nature of the data, must assume that preferences are equal across villages otherwise. The only study that uses panel data to disentangle the cross-sectional and time-series elasticities of risk aversion to wealth is Chiappori and Paiella (2008). In their case, however, changes in agent's wealth are not exogenous, and they find the bias from the cross sectional estimation to be economically insignificant. In contrast, the bias would lead to severely underestimate the elasticity of the investor-specific risk aversion to wealth in our setting.

The existing evidence on the link between risk aversion and wealth in the cross section is inconclusive. When the risk aversion parameters are estimated from the share of risky and riskless assets, the sign of the correlation between risk aversion and wealth is sensitive to the definition of wealth and the categorization of assets into risky and riskless (see, among others, Blume and Friend (1975), Cohn, Lewellen, Lease and Schlarbaum (1975), Morin and Suarez (1983), and Blake (1996)). Guiso and Paiella (2008) and Cicchetti and Dubin (1994) avoid

[5]Net worth is imputed by Acxiom, a third party specialized in recovering consumer demographics based on public data.

this problem by estimating risk aversion from answers to an hypothetical lottery and data on insurance against phone line troubles, respectively. Both studies find, as we do, a positive cross sectional correlation between relative risk aversion and wealth.

We test whether the estimated level and wealth elasticity of risk aversion are consistent across investors' decisions in LC: the total amount to invest in LC, the loans to include in the portfolio, and the portfolio allocation across these loans. We test the consistency of the estimated *level* of risk aversion using a revealed preference argument. The median investor has in her portfolio only a subset of the loans available at the time of her investment decision. We find, using the preferences estimated from the loans in an investor's portfolio, that including the foregone loans in the portfolio would lower her expected utility. Second, we test whether the cross-sectional and within-investor *elasticities* of risk aversion to wealth consistently extrapolate to the investor's decision of how much to invest in LC. In the expected utility framework, when relative risk aversion decreases (increases) in outside wealth, the share of wealth invested in LC will increase (decrease) in outside wealth. The point estimates of the wealth elasticities of investment in LC corroborate these predictions both in the cross section of investors and within investor.

The rest of the paper is organized as follows. Section 2 describes the Lending Club platform. Section 3 solves the portfolio choice model and sets out our estimation strategy. Section 4 describes the data and the sample restrictions. Section 5 presents and discusses the empirical results and provides a test of the identification assumptions. Section 6 explores the relationship between risk preferences 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 May 2010 it has funded \$112,003,250 in loans and provided an average net annualized return of 9.64% to investors.[6]

[6] For the latest figures refer to: https://www.lendingclub.com/info/statistics.action.

Below, we provide an overview of the platform 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 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, and it is posted on the website.[7] 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. It becomes a loan only if it attracts enough investors and gets fully funded. 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 ranging from 1.25% to 3.75% depending on the credit bucket. 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

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

returns relative to alternative investment opportunities are the main motivations for investing in LC.[8] LC lowers the cost of investment diversification inside LC by providing an optimization tool that constructs the set of efficient loan portfolios for the investor's overall amount invested in LC—i.e., the minimum idiosyncratic variance for each level of expected return (see Figure 1). In other words, the tool helps investors to process the information on interest rates and default probabilities posted in the website into measures of expected return and idiosyncratic variance, that may otherwise be difficult to compute for an average investor (these computations are performed in Subsection 2.2).[9] When investors use the tool, they select, among all the efficient portfolios, the preferred one according to their own risk preferences. Investors can also use the tool's recommendation as a starting point and then make alterations. Or they can simply select the loans in their portfolio manually.

Of all portfolio allocations between LC's inception and 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.[10]

Given two loans that belong to the same risk bucket (with the same idiosyncratic risk), the optimization tool suggests the one with the highest fraction of the requested amount that is already funded. This tie-breaking rule maximizes the likelihood that loans chosen by investors are fully funded. In addition, if a loan is partially funded at the time the application expires, LC provides the remaining funds.

2.2 Return and Variance of the Risk Buckets

All the loans in a given risk bucket $z = 1, ..., 35$ are characterized by the same scheduled monthly payment per borrowed dollar P_z over the 3 years (36 monthly installments). The per dollar

[8] To 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". 62% of respondents also chose diversification and higher returns as their secondary reason for joining Lending Club.

[9] The tool normalizes the idiosyncratic variance into a 1–0 scale. 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.

[10] We exploit this variation in Subsection 5.2 to validate the identification assumptions.

scheduled payment P_z and the bucket specific default rate π_z fully characterize the expected return and variance of *per project* investments, μ_z and σ_z^2.

LC considers a geometric distribution for the idiosyncratic monthly survival probability of the individual projects, $\Pr(T=\tau)=\pi_z(1-\pi_z)^\tau$ for $T \in [1,36]$. The resulting expected value and variance of the return (in present value) of a project in bucket z are:

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

where r is the risk-free interest rate. Although LC considers all risk to be idiosyncratic, our estimations are not affected by the introduction of a non-diversifiable risk component, V_z. The resulting variance of the return on investment in bucket z is given by:

$$var\left[R_z^i\right]=V_z+var\left[r_z^i\right]$$

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

Since the π_z captures the idiosyncratic probability of default of the loans in risk bucket z, the returns are, by construction, independent. The idiosyncratic risk associated with bucket z decreases with the level of diversification within the bucket; that is, the number of projects from bucket z in the portfolio of investor i, n_z^i. The resulting idiosyncratic variance is therefore investor specific:

$$var\left[r_z^i\right]=\frac{1}{n_z^i}\sigma_z^2. \tag{1}$$

The expected return of an investment in bucket z is not affected by the number of loans in the investor's portfolio and is equal to the expected return of the representative project, μ_z:

$$E\left[R_z^i\right]=\mu_z. \tag{2}$$

3 Estimation Procedure

The portfolio model in this section is based on Treynor and Black (1973). This framework considers investors that, instead of simply holding a replica of the market portfolio, also hold securities based on their own subjective *insights*.

Person-to-person lending markets, including LC, are not well known investment vehicles among the general public. The selection of investors into this program is potentially related to their information on the existence of the platform, together with their subjective expectation that LC is, indeed, a good investment opportunity. In other words, investors in LC have special *insights*, which explains why their portfolio departs from just replicating the market; exactly the case considered in Treynor and Black (1973).

This theoretical framework starts by recognizing that there is high degree of co-movement between securities, and specifically to our case, the probability of default of all loans in LC is potentially correlated with macreoconomic fluctuations. We use Shape's Diagonal Model of covariance among securities. It assumes that returns of securities are related only through a common systematic factor (i.e., market or macroeconomic fluctuations). Under this assumption, returns of LC loans can be decomposed into this common systematic factor and a pure idiosyncratic component (we also refer to it as *independent* return).

The virtue of the model developed here is that the optimal portfolio depends only on the expected return and variance of the idiosyncratic component. In other words, the optimal amount invested in each LC loan 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. The optimal portfolio is such that the investor is indifferent about allocating an extra dollar in a riskier bucket: the extra idiosyncratic risk would be exactly compensated by the increase in expected return, given the risk aversion of the investor. Based on this optimality condition, and having computed the expected return and the variance of the loans idiosyncratic risk in Subsection 2.2, we infer the investor specific risk aversion.

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 that are part of the active portfolio of the investor, with return R_z.

We consider investments in LC as part of the active portfolio. We also allow for the existence of unobservable outside active risky investments. That is, the 35 risk buckets in LC are denote $z = 1, ..., 35$, with $35 \leq Z$.[11] The resulting portfolio of investor i is

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

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

$$R_z = \beta_z^i \cdot R_m + r_z \tag{4}$$

We consider all risk buckets to have the same systematic component, and allow the prior about the market sensitivity of LC returns to be investor specific. That is, for all $z = 1, ..., 35$: $\beta_z^i = \beta_L^i$. This assumption is tested in Subsection 5.2.[12]

Note that, by construction, the residual return r_z is independent from the market's behavior:

$$cov\left[R_m; r_z\right] = 0.$$

[11] In an alternative hypothesis, participants in LC do not have special insights and their investment in LC is not part of the active component but only a fraction of the market portfolio. In that case, the composition of risk buckets within LC is not given by the investor's risk aversion, as the optimal shares in the market portfolio are constant across investors. This hypothesis is strongly rejected by the data in the results section.

[12] Note 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 $V_z^i = \left(\beta_L^i\right)^2 \cdot var\left[R_m\right]$, for all $z = 1, ..., 35$.

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

$$c^i = W^i \left[x^i_f + x^i_{Z+1} R_m + \sum_{z=1}^{Z} x^i_z r_z \right] \tag{5}$$

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

$$x^i_{Z+1} = x^i_m + \sum_{z=1}^{Z} x^i_z \beta_z \tag{6}$$

We use Sharpe's Diagonal Model for covariance among securities. It posits that the returns of the different investment opportunities are related to each other only through their relationships with a common underlying factor. In the case of LC, the loans in the program are assumed to be related to other securities only through the market's effect on LC systematic risk. That is, the independent returns, defined in equation (4), are uncorrelated.

Assumption 1. *Sharpe's Diagonal Model*[13]

$$\textit{for all } n \neq h : \textit{cov}\left[r_n, r_h\right] = 0$$

To grasp the intuition behind this assumption, it is useful to consider examples of bucket risk properties that, both, fulfill and violate Sharpe's Diagonal Model. Macroeconomic fluctuations, such as the sub-prime financial crisis, can trigger general defaults across buckets. This example represents an underlying common factor, identified in the systematic component of equation (4), and satisfies our assumption. On the other hand, Sharpe's Diagonal Model may be violated if risk buckets are correlated with investor-specific risk. If that is the case, investors would not behave as described in this portfolio model. Instead, they would choose those risk buckets that provide hedging against their unobservable specific risk. A natural example in our context is hedging associated with geographical location. We find in unreported results (available upon

[13] Allowing a time dimension, the independent returns are also uncorrelated across time. That is, the portfolio choices within LC are time-independent.

request) that there is no systematic variation across buckets in the geographical distance between borrowers and investors.

Under assumption 1, our theoretical framework transforms the original investor budget constraint in equation (3) into the portfolio in equation (5), composed of a risk-free asset and $Z+1$ mutually independent securities. We begin by considering the expected utility framework over total wealth; in Appendix A we discuss the implications of alternative preferences (i.e., loss aversion and narrow framing). The investor is constrained to non-negative positions in all the LC buckets: $x_z \geq 0$ for $z = 1, ..., 35$. The following problem describes the portfolio choice of investor i:

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

For all active buckets with $x_z > 0$, the first order condition characterizing the optimal portfolio share is:[14]

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

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

$$E\left[r_z\right] - 1 = \left(-\frac{u''\left(E\left[c^i\right]\right)}{u'\left(E\left[c^i\right]\right)}\right) \cdot W^i x_z^i \cdot var\left[r_z\right]. \tag{7}$$

Note that, even when LC projects are affected by market fluctuations, the optimal investment in bucket z is independent of market risk considerations, or the volatility 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 imbedded 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.

Rewriting investor specific idiosyncratic risk in terms of the common parameter σ_z, computed

[14]The minimum investment per loan is $25. This limit results in discrete intervals over which the number of projects financed, n_z^i, is unaltered by a marginal change in x_z. The following first order condition characterizes the optimal portfolio within these discrete intervals.

in equation (1), and substituting the expectation of the independent return, $E[r_z]$, with the observable expected return $E[R_z]$, computed in equation (2), we derive our main empirical equation. Let A^i be the set of all active risk buckets —i.e. $A^i = \left\{z \leq 35 | x_z^i > 0\right\}$ −, then for all $z \in A^i$:

$$E[R_z] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \sigma_z^2 \tag{8}$$

The parameter θ^i collects the systematic component of the LC investment, which is constant across buckets. We estimate this parameter as a person specific constant. Thus, our estimation procedure does not require the computation of the LC portfolio covariance with the market. Although our main estimation procedure exploits only the active risk buckets ($z \in A^i$), we show in Subsection 7.1 that the estimated risk preferences are consistent with those implied by the forgone buckets ($z \notin A^i$).

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:

$$\theta^i \equiv 1 + \beta_L^i E[R_m] \tag{9}$$

$$ARA^i \equiv -\frac{u''\left(E\left[c^i\right]\right)}{u'\left(E\left[c^i\right]\right)} \tag{10}$$

It is shown in Appendix A that the same empirical equation characterizes the optimal LC portfolio when investors are averse to losses in their overall wealth. Moreover, a similar result is derived from a behavioral model where investors' preferences within LC are independent from their attitude towards risk in other settings. However, we show in Subsection 7.2 that this is not the case; information recovered from this first order condition is relevant for understanding other investor decisions within LC.

The expected lifetime wealth of the investors is unknown and we therefore cannot compute the Relative Risk Aversion (RRA). However, for the purpose of comparing our estimates with results from laboratory experiments, we follow that literature and define a relative risk aversion based solely on the income generated by investing in LC, which we denote ρ (see, for example, Holt and Laury (2002)):

$$\rho^i \equiv ARA^i \cdot I_L^i \cdot \left(E\left[R_L^i\right] - 1\right) \tag{11}$$

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

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, and 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 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 faction 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 then 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 (2010), 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.[15] The full sample contains 2,168 investors, 5,191 portfolio choices, which results in 50,254 investment-bucket observations. Table 2, panel A, reports the descriptive statistics of the investment-buckets. The median expected return is 12.2%, with a 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 0.0054% thanks 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 (8).

[15] This 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.

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 further 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 (8). We allow for an additive error term, such that for each investor i we estimate the following equation:

$$E\left[R_z\right] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \sigma_z^2 + \varepsilon_z^i \tag{12}$$

There is one independent equation for each active bucket z 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 (12) with Ordinary Least Squares.

Figure 3 shows four examples of portfolio choices. The vertical axis measures the expected return of a risk bucket, $E\left[R_z\right]$, 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 error term captures deviations from the efficient portfolio due to the \$25 constraint for the minimum investment, measurement errors by investors, and real or perceived private information of the investors. 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 below.

5.1 Results

The descriptive statistics of the estimated parameters of equation (8) for each portfolio choice are presented in Table 3. The average estimated ARA across all portfolio choices is 0.0368. Investors exhibit substantial heterogeneity in risk aversion, and its distribution is left skewed: the median ARA is 0.0439 and the standard deviation 0.0246. This 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 (2009), 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.[16] The range of the ARA estimates is consistent with the estimates recovered in the laboratory. Holt and Laury (2002), for example, obtain ARA estimates between 0.003 and 0.109 depending on the size of the bet.

The experimental literature often reports the income-based RRA, defined in equation (11). To compare our results with those of laboratory participants, we report the distribution of the implied income-based RRA in Table 3. The mean income-based RRA 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. Table 3 reports the distribution of expected income from LC. The mean expected income is $130, substantially higher than the bet in most laboratory experiments. Not surprisingly, although the computed ARA in experimental work is typically larger than our estimates, the income-based RRA parameter is smaller, ranging from 0.3 to 0.52 (see for example Chen and Plott (1998), Goeree, Holt and Palfrey (2002), Goeree, Holt and Palfrey (2003), and Goeree and Holt (2004)). Our results are comparable to Holt and Laury (2002), who also estimate risk aversion for agents facing large bets and (implicitly) find income-based RRA similar to ours, 1.2. Finally, Choi et al. (2007) report risk premia with a mean of 0.9, which corresponds to an income-based RRA of 1.8 in our setting. That paper also finds right skewness in their measure of risk premia.

Our findings imply that the high levels of risk aversion exhibited by experimental subjects extrapolate to actual small-stake investment choices. Rabin and Thaler (2001) and Rabin and Thaler (2002) emphasize that such levels of risk aversion with small stakes are difficult to rec-

[16]The variance of the true ARA is calculated as:

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

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.

oncile, within the expected utility framework over total wealth, with the observable behavior of agents in environments with larger stakes. Still, we show in the next section that the shape of the utility function recovered from investor behavior in small stake environments provides useful information about the behavior of investors when facing different decisions; namely, the total amount to invest in LC relative to other investment opportunities.

The parameter θ, defined in equation (9), collects the systematic component of LC. In our framework, the systematic component is driven by the common covariance between all LC bucket returns and the market, β_L. 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%).[17] This suggests that agents agree in their priors about the systematic risk imbedded in the LC investment. Note that our ARA estimates are not based on this risk premium; instead, they are based on the marginal premium required to take an epsilon grater risk.

5.2 Belief Heterogeneity and Bias: The Optimization Tool

Above we interpret the observed heterogeneity of investor portfolio choices as arising from differences in risk preferences. Such heterogeneity may also arise if investors have different beliefs about the risk and returns of the 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. The evidence in the previous section suggests that investors have relatively common priors about this systematic component of the returns, i.e., common priors about LC's beta, β_L.

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 $z = 1, ..., 35$; or if investors'

[17] As with the ARA, the estimation variance is small relative to the variance across investments. The standard deviation of $\hat{\theta}$ is 0.0269, while the standard deviation of θ after subtracting the estimation variance is 0.0260.

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 $z = 1, ..., 35$. In such cases, the equation characterizing the investor's optimal portfolio is given by:

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

This expression differs from our main specification equation (8) in three bias terms: $B_\sigma \equiv \left(\sigma_z^i/\sigma_z\right)^2$, $B_\mu \equiv \left(E[R_z] - E^i[R_z]\right) / \left(W^i x_z^i \sigma_z^2 / n_z^i\right)$, and $B_\beta \equiv \left(\beta_z^i - \beta_L^i\right) / (W^i x_z^i \sigma_z^2 / n_z^i)$.

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. $\beta_z = \beta_L$.[18]

Thus, we can measure the estimation bias by comparing the estimation based on choices suggested by the tool, to those portfolio choices made without the tool. 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, investor preferences will be consistent across the two measures. 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. 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.

[18]See Appendix B for the derivation of the efficient portfolios suggested by the optimization tool.

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 4, panel A, reports the descriptive statistics of the estimated ARA using for each investment the Automatic and the Non-Automatic buckets independently. The average ARA is virtually identical across the two estimations (Table 4, columns 1 and 2), and the means are statistically indistinguishable at the 1% level. This implies that, if there is a bias 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 substantially from those posted on the website. 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 4, 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.[19]

Table 4, 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. The mean difference is not statistically difference at the 1% confidence level. This suggests that our estimates of the risk premium are unbiased.[20]

Finally, it is worth emphasizing 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, panels B and C of Table 4 suggest that the average estimated risk premium increases by 2.5 percentage points during the second part of the sample. Such change can be driven by an increase in the expected market risk premium or an increase in the perceived covariance of LC returns with the market. The results in Table 4 imply that changes in investors' beliefs are fully accounted for by a common systematic component across all risk buckets and, thus, do not bias our risk aversion estimates.

[19] We also verify, but exclude for brevity, that the average Automatic versus Non-Automatic ARA difference does not vary significantly across risk buckets. This rules out, for example, that investors beliefs coincide with those posted in LC for low risk borrowers but differ for high risk borrowers.

[20] In Appendix B we show that a bias in the risk premia estimate may arise because the optimization tool's suggestion is potentially suboptimal relative to the one implied by condition (8). The intuition is that, for any given return, condition (8) minimizes the variance of the investor's entire risky portfolio, while the optimization tool minimizes the variance of the LC portion of her portfolio only. The results imply that the inclusion of the Automatic component of investments does not bias our estimations and further validates the conclusions of this section.

6 Risk Aversion and Wealth

This section explores the relationship between risk taking behavior and investors' wealth. We estimate the elasticity of ARA and two separate measures of RRA with respect to wealth. One estimate of this elasticity corresponds to the income-based RRA in equation (11). The other corresponds to the wealth-based RRA ($RRA^i = ARA^i W^i$). The wealth-based RRA is not directly observable, but its elasticity is computed based on the elasticity of ARA with respect to wealth:

$$\xi_{RRA,W} = \xi_{ARA,W} + 1, \tag{13}$$

where $\xi_{RRA,W}$ and $\xi_{ARA,W}$ refer to the wealth elasticities of RRA and ARA, respectively. Similarly, we refer to $\xi_{\rho,W}$ as the elasticity of income-based RRA with respect to wealth.

We exploit the panel dimension of our data and estimate these elasticities, both, in the cross section of investors and, for a given investor, in the time series. In the cross section, wealthier investors exhibit lower ARA and higher RRA when choosing their portfolio of loans within LC. And, in the time series, investor specific RRA increases after experiencing a negative wealth shock; that is, the preference function exhibits decreasing RRA. The contrasting signs of the cross sectional and investor-specific wealth elasticities indicate that preferences and wealth are not independently distributed among investors.

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.

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.[21] 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.[22]

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. 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

[21] According 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, Kennickel, Mach and Moore (2009)).

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

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.[23] 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. Absolute risk aversion is decreasing in both wealth proxies, while income-based relative risk aversion is increasing.

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

$$\ln\left(RiskAversion_i\right) = \beta_0 + \beta_1 \ln\left(NetWorth_i\right) + \omega_i. \tag{14}$$

The left hand side variable is investor i's average (log) risk aversion, obtained by averaging the risk aversion estimates recovered from the investor's portfolio choices during our sample period. We use both ARA and income-based RRA as alternative measures of investor risk aversion. The right-hand side variable is investor i's imputed net worth. Thus, the estimated β_1 corresponds to the wealth elasticities of ARA and income-based RRA, respectively —i.e., $\xi_{ARA,W}$ and $\xi_{\rho,W}$–.

[23] The cross sectional results are unchanged when we include renters. We condition on home owners so that the same investor sample is used in the cross sectional and within-investor estimations.

To account for measurement error in our wealth proxy we estimate specification (14) 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 (14) to be clustered by zip code.

Table 5 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 5, column 1). The non-parametric relationships are confirmed: wealthier investors exhibit a lower ARA. Column 2 shows that 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 OLS elasticity estimates are always biased towards zero. This attenuation bias is consistent with classical measurement error in the wealth proxy.

The estimated ARA elasticity and equation (13) imply that the wealth-based RRA elasticity to wealth is positive, $\widehat{\xi}_{RRA,W} = 0.94$. This coincides with the sign of the income-based RRA elasticity. Thus, the different estimates consistently indicate that the RRA is larger for wealthier investors in the cross section. These cross sectional results coincide with Guiso and Paiella (2008), who estimate risk aversion parameters from agents' answers to an hypothetical lottery in a survey of Italian households, and find that wealthier investors exhibit lower ARA and higher RRA.

6.3 Within-Investor Estimates

The above elasticity, obtained from the variation of risk aversion and wealth in the cross section, can be taken to represent the form of the utility function of the representative investor only under strong assumptions. Namely, when the joint distribution of wealth and preferences in the population are independent.[24] To identify the functional form of individual risk preferences we

[24] Chiappori and Paiella (2008) 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.

estimate the risk aversion elasticity using within-investor time series variation in wealth:

$$\ln (RiskAversion_{it}) = \alpha_i + \beta_2 \ln (HouseValue_{it}) + \omega_{it}. \quad (15)$$

The left-hand side variable is the estimated measure of risk aversion for investor i in month t (ARA and income-based RRA). 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 (15) 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 risk aversion to investor-specific shocks to wealth.

The parameter β_2 is estimated only from changes in the risk aversion 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 (15) comes from less than half of the original sample. To insure that the results below are representative for the full investor sample, we confirm that the results obtained in the previous sub-section are unchanged when estimated on the subsample of investors that chose portfolios more than once (unreported).

Table 6 reports the parameter estimates of specification (15), before and after including the investor FE (Panels A and B respectively). The FE results represent our estimated wealth elasticities of ARA and the income-based RRA—i.e. $\xi_{ARA,W}$ and $\xi_{\rho,W}$, respectively. 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. Column 2 reports the estimated elasticity of the income-based RRA. It is negative and both statistically and economically significant. The point estimate of -4.18 indicates that the average investor's income-based RRA increases from 2.85 to 3.33 when she experiences a 4% decline in house prices in her zip code, the sample average.

Again, using equation (13), we use the estimated wealth elasticity of ARA to calculate the elasticity of the wealth-based RRA to wealth changes for a given investor. The implied elasticity is negative, $\xi_{RRA,W} = -1.82$, which coincides with the estimated sign of the income-based RRA elasticity. 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. 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.[25] This is unlikely in our setting since stock prices dropped 10% and investments in bonds had a positive yield during our sample period.[26] Therefore, even if measurement error biases the numerical estimate, it is unlikely to affect our conclusions regarding the shape of the utility function.

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 6 confirms this. 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 the be wealthier and to be more risk averse. The results indicate that characterizing empirically the shape of the utility function requires, first, accounting for such

[25] We 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 implies $\frac{d \ln W}{d \ln H} > 2.82$.

[26] Between 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%.

heterogeneity.

Our results are consistent with those in Tanaka et al. (2010), based on a field experiment in a cross section of households in Vietnam. That study uses heterogeneous rainfall across villages as an instrument for wealth, but due to the cross sectional nature of the data, must assume that preferences were equal across villages otherwise. Chiappori and Paiella (2008), on the other hand, find RRA to be constant to wealth shocks (i.e., CRRA). However, they estimate risk aversion parameters from the share of wealth invested in risky assets in a panel of households, and their conclusion is sensitive to the definitions of the risky and riskless portions.

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.

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. We show in this subsection that including the *foregone* buckets in the median 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 (12) characterizes the allocation of the median investment among the 10 active buckets without using the corresponding equations describing the choice of the foregone 25 buckets. We use these conditions to develop a consistency test for investors' choices.

For each investor i, let A^i be the set of active risk buckets. The optimal portfolio model described in Section 3, predicts that, for all foregone risk buckets $z \notin A^i$, the first order condition (8), evaluated at the minimum investment amount per project of \$25, is negative—i.e. the nonnegative constraint is binding. The resulting linearized condition for all $z \notin A^i$ is:

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

We test this prediction by calculating $foc_{foregone}$ for every foregone bucket using the parameters $\left\{\theta = \hat{\theta}^i, ARA^i = \widehat{ARA}^i\right\}$ estimated with specification (12). 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 (12). 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 cross-sectional and within-investor *elasticities* of risk aversion to wealth consistently extrapolate to the investor's decision of how much to invest in LC. Our model in Section 3 delivers testable implications for the relationship between an investor's risk preferences and her overall holdings of the efficient LC portfolio. Namely, when relative risk aversion decreases (increases) in wealth, then the share of wealth invested in LC will increase (decrease) in wealth (see Appendix C). We can use these predictions, both, to provide an independent validation for the results on the elasticity of risk aversion to wealth based on the risk aversion estimates obtained in Section 5, and to explore the connection between investors' risk preferences across different types of choices.

We test the above implications by estimating specifications (14) and (15) using the (log) amount invested in LC as dependent variable. Table 5 and 6 (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 5, column 3). The elasticity is smaller than one, which suggests that the ratio of the investment to wealth is decreasing. These estimates are consistent with decreasing ARA and increasing RRA cross sectional elasticities reported in Tables 5. 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 grater than one when we add investor fixed effects (Table 5 column 3). This implies that, for a given investor, the ratio of investment to wealth is increasing. 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 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 opportunities.

Providing evidence of this link is impossible in a laboratory environment where the investment amount is exogenously fixed by the experiment design. Our results suggest that preference parameters obtained from marginal choices can plausibly explain decision making behavior in broader contexts.

8 Conclusion

In this paper we estimate risk preference 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. The average absolute risk aversion in our sample is 0.0368. We also measure the relative risk aversion based on the income generated by investing in LC. We find a large degree of heterogeneity, with an average income-based relative risk aversion of 2.85 and a median of 1.62. These findings are similar to those obtained in laboratory studies, suggesting that experimental results extrapolate to real life investment choices.

We exploit the panel dimension of our data and estimate the elasticity of ARA and RRA with respect to wealth, both, in the cross section of investors and, for a given investor, in the time series. In the cross section, wealthier investors exhibit lower ARA and higher RRA when choosing their portfolio of loans within LC. And, in the time series, investor specific RRA increases after experiencing a negative wealth shock; that is, the preference function exhibits decreasing RRA. The contrasting signs of the cross sectional and investor-specific wealth elasticities indicates that investors preferences and wealth are not independently distributed in the cross section. The results indicate that characterizing empirically the shape of the utility function requires, first, accounting for such heterogeneity.

Parallel to experimental results, the observed levels of risk aversion inside LC are difficult to reconcile with reasonable choices in large stake environment, when agents maximize expected utility over total wealth.[27] A natural question, then, is whether the risk taking behavior within LC is connected with investors' preferences in broader contexts. We find evidence in support of this hypothesis: investors in LC exhibit decreasing relative risk aversion and this functional form extrapolates to their decision of how much to invest in LC. We therefore conclude that the *sensitivity* of risk aversion to wealth obtained in a small-stake environment extrapolates to other investor decisions even if the *level* of risk aversion does not.

[27] This is commonly referred to as the *Rabin's Critique* (Rabin (2000) and Rabin and Thaler (2001)). See also Rubinstein (2001) for an alternative interpretation of this phenomenon within the expected utility theory.

We explore whether utility functions outside the expected utility family can account for this phenomenon. Since outside wealth affects risk taking behavior in LC, the findings are not consistent with frameworks in which preferences are separable over different components of the investors' wealth (narrow framing). Also, since LC is a small portion of the agent's wealth and the return of given project has negligible impact on the overall distribution of wealth, the observed levels of risk aversion cannot be explained by loss aversion over changes in total wealth. Our findings are consistent with a 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 agent's portfolio. This is in line with Barberis and Huang (2001) and Barberis, Huang and Thaler (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. We leave the exploration of these alternatives in the LC environment for future research.

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Appendix

A Non-Expected Utility Frameworks

A.1 Loss Aversion over Changes in Overall Wealth

Consider the following preferences, which exhibit loss aversion with coefficient α around a benchmark consumption $\overline{c}$

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

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 $\omega = c - Wx_z r_z$, 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:

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

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

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

Replacing, the first order condition is approximated by:

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

This condition is equivalent to the one in the body of the paper, irrespectively of the value of $\overline{c}$ 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*:

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

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

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.

A.2 Narrow Framing

Consider the following preferences:

$$U = \sum_{k=1}^{K} E\left[u_k\left(I_k^i R_k\right)\right]$$

$k = 1, ..., K$ corresponds to the different sub-portfolios over which the investor exhibits local preferences; I_k and R_k are the total amount allocated in each of these sub-portfolios and the corresponding return.

Consider LC to be one of these sub-portfolios, so for $k = L$, the investor chooses the shares $\{x_z\}_{z=1}^{35}$ to be invested in each risk bucket so to maximize her utility over LC, for a given amount invested in the program, I_L^i: $E\left[u_L\left(I_L^i \cdot \sum_{z=1}^{35} x_z^i R_z\right)\right]$

The first order condition that characterizes all active buckets is:

$$foc(x_z) : E\left[u_L'\left(I_L^i \cdot \sum_{z=1}^{35} x_z^i R_z\right) R_z\right] - \mu_L^i = 0$$

where μ_L^i is the multiplier on the budget constraint $\sum_{z=1}^{35} x_z^i = 1$.

A linearization around expected return results in the following expression:

$$u_L'\left(I_L^i E\left[R_L\right]\right) E\left[R_z\right] + u_L''\left(I_L^i E\left[R_{LC}\right]\right) I_L^i \sum_{z=1}^{35} x_z^i E\left[\left(R_z - E\left[R_z\right]\right) \cdot R_z\right] = \mu_L^i$$

From equation (4) and assuming $\beta_z^i = \beta_L^i$, the returns in LC are decomposed into a common systematic factor $\beta_L^i R_m$ and an idiosyncratic component r_z. Moreover, under the Diagonal Sharpe's Ratio in Assumptions 1, returns from different buckets co-move only through their market component. That is:

$$\begin{aligned} for\ all\ z \neq z' \quad : \quad & E\left[\left(R_{z'} - E\left[R_{z'}\right]\right) R_z\right] = (\beta_L^i)^2 var\left[R_m\right] \\ & E\left[\left(R_z - E\left[R_z\right]\right) R_z\right] = (\beta_L^i)^2 var\left[R_m\right] + var\left[r_z\right] \end{aligned}$$

Replacing, the optimal portfolio within LC is characterized by the following expression:

$$u_L'\left(I_L^i E\left[R_L\right]\right) E\left[R_z\right] + u_L''\left(I_L^i E\left[R_L\right]\right) I_L \left((\beta_L^i)^2 var\left[R_m\right] + x_z var\left[r_z\right]\right) = \mu_L^i$$

Rearranging terms, this leads to the same empirical equation as in the body of the paper:

$$E\left[R_z\right] = \theta^i + ARA_L^i \cdot I_L^i x_z^i \cdot var\left[r_z\right]$$

$I_L^i x_z^i$ is the total amount invested in bucket z, equivalent to $W^i x_z^i$ in the body of the paper. Note that the systematic component is common to all risk buckets and therefore does not alter the portfolio composition within LC. It is recovered by the investor specific constant, which is given in this framework by:

$$\theta^i \equiv \frac{\mu_L^i}{u'\left(I_L^i E\left[R_L\right]\right)} - ARA_L^i \cdot I_L^i \cdot (\beta_L^i)^2 var\left[R_m\right]$$

If investors behave according to these preferences the ARA obtained from this empirical equation only characterize the preferences within LC, u_L, for a given amount invested in the program, I_L:

$$ARA_L^i \equiv -\frac{u_L''\left(I_L^i E\left[R_L\right]\right)}{u_L'\left(I_L^i E\left[R_L\right]\right)}.$$

However, we show in the paper that this is not the case. The shape of the utility that follows from investors' choices within LC extrapolates to other decisions. In particular, the amount invested in LC: I_L. Moreover, follows from this expression, that if investors exhibit *narrow framing*, realizations of returns in other sub-portfolios $k \neq L$ do not affect risk preferences ARA_L^i. We show that this is not the case; changes in the value of the investors' house affect the preferences exhibited within LC.

B 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 (7):

$$E\left[r_L\right] - 1 = ARA^i \cdot W^i x_L^i \cdot var\left[r_L\right] \tag{A.1}$$

$\left(E\left[r_L\right] - 1\right)/var\left[r_L\right]$ 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 $z = 1, ..., 35$ satisfies the following program:

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

$var\left[r_z\right]$ and $E\left[R_z\right]$ are the idiosyncratic variance and expected return of the (optimally diversified) risk bucket z, computed in equations (1) and (2); and $E\left[R_L\right]$ 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, $E\left[r_L\right]$. That is, the problem is not affected by subtracting a common systematic component, $\beta_L E\left[R_m\right]$ on both sides of the expectation constraint. The resulting efficient portfolio suggested by the website satisfies the following condition for every active bucket z, for which $s_z > 0$:

$$s_z = \lambda_0^i \frac{E\left[r_z\right] - \lambda_1^i}{var\left[r_z\right]} \tag{A.2}$$

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:

$$\lambda_0^i = \frac{var\left[r_L\right]}{E\left[r_L\right] - \lambda_1^i} \tag{A.3}$$

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

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

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 (12) may be biased by the inclusion of the *Automatic* choices. The magnitude of the bias is:

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

where θ_N^i and θ_A^i correspond to the investor specific constant in the specification equations (8) and (A.4) respectively:

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

We find that the intercepts estimated from *Automatic* and *Non-Automatic* choices (θ_A and θ_N)

are equal (see Table 4). We therefore conclude that including *Automatic* choices does not bias our results.

C 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:

$$\max_{x} Eu\left(W^i\left(x_f^i + x_m^i R_m + x_L^i R_L\right)\right)$$

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 (8): $R_L = \sum_{z=1}^{Z_L} \widetilde{x}_z R_z$ where $\widetilde{x}_z \equiv x_z / \sum_{z=1}^{35} x_z$. 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 $c^i = W^i\left(x_f^i + \widetilde{x}_m^i R_m + x_L^i r_L\right)$, where $\widetilde{x}_m^i = x_m^i + x_L^i \beta_L^i$ 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:

$$E\left[R_L\right] = \theta^i + ARA^i \cdot I_L^i \cdot var\left[r_L\right]$$

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:

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

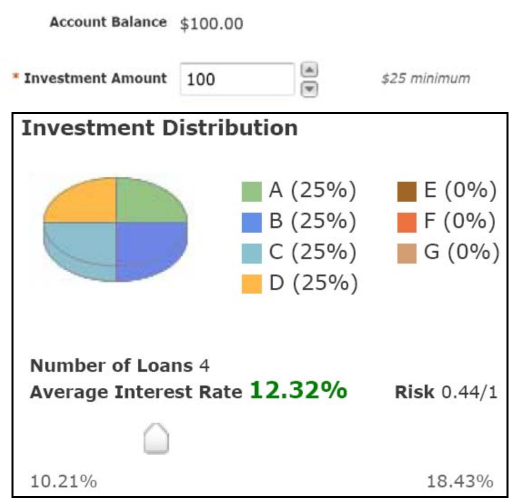
ARA and RRA refer to absolute and wealth-based relative risk aversion: $ARA \equiv -\frac{u''\left(E[c^i]\right)}{u'(E[c^i])}$ and $RRA \equiv -\frac{u''\left(E[c^i]\right)}{u'(E[c^i])} W$. We obtain the following testable implications:

Result 1. *If the absolute risk aversion, ARA, decreases (increases) in outside wealth, then the amount invested in LC, I_L, increases (decreases) in outside wealth.*

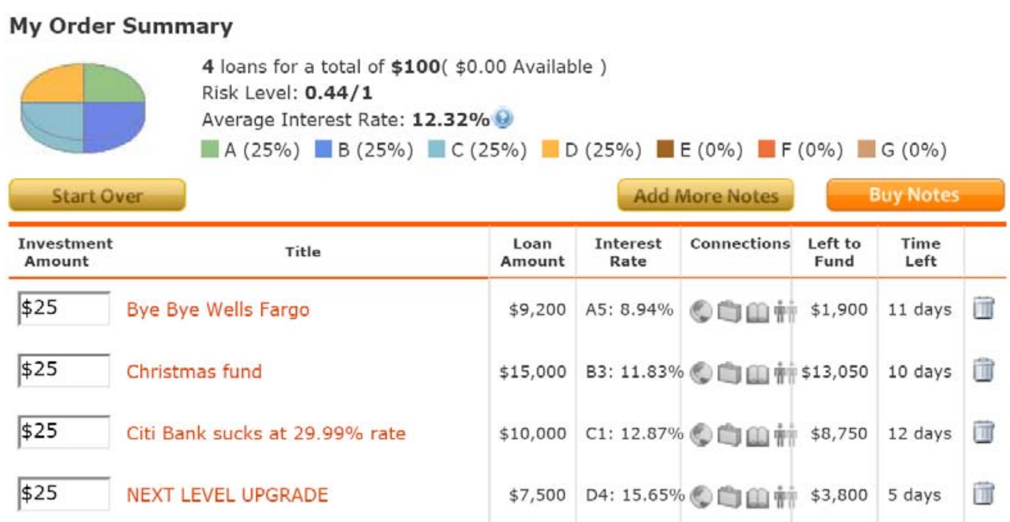
Result 2. *If the wealth-based RRA decreases (increases) in outside wealth, then the share of wealth invested in LC, I_L/W, increases (decreases) in outside wealth.*

We test these implications by estimating specifications (14) and (15) using the (log) amount invested in LC.

A. Screen 1: Interest rate – Normalized Variance "Slider"

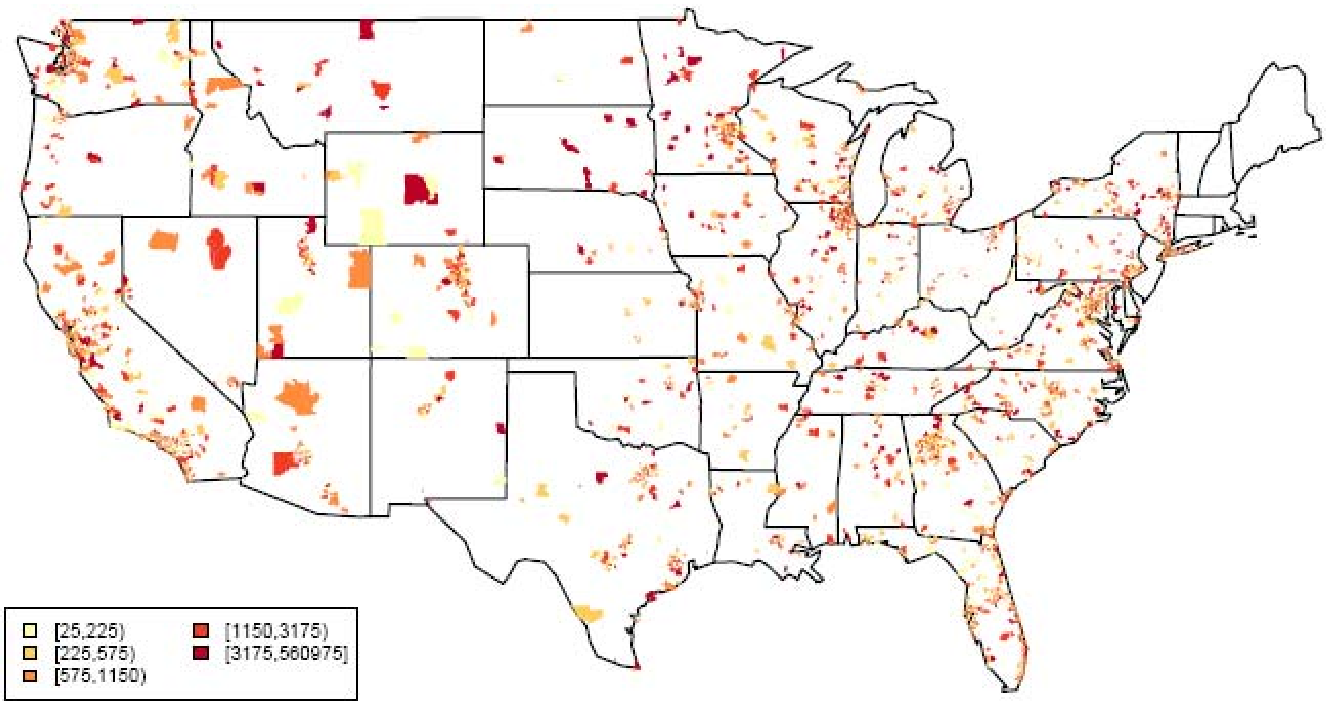


B. Screen 2: Suggested Portfolio Summary



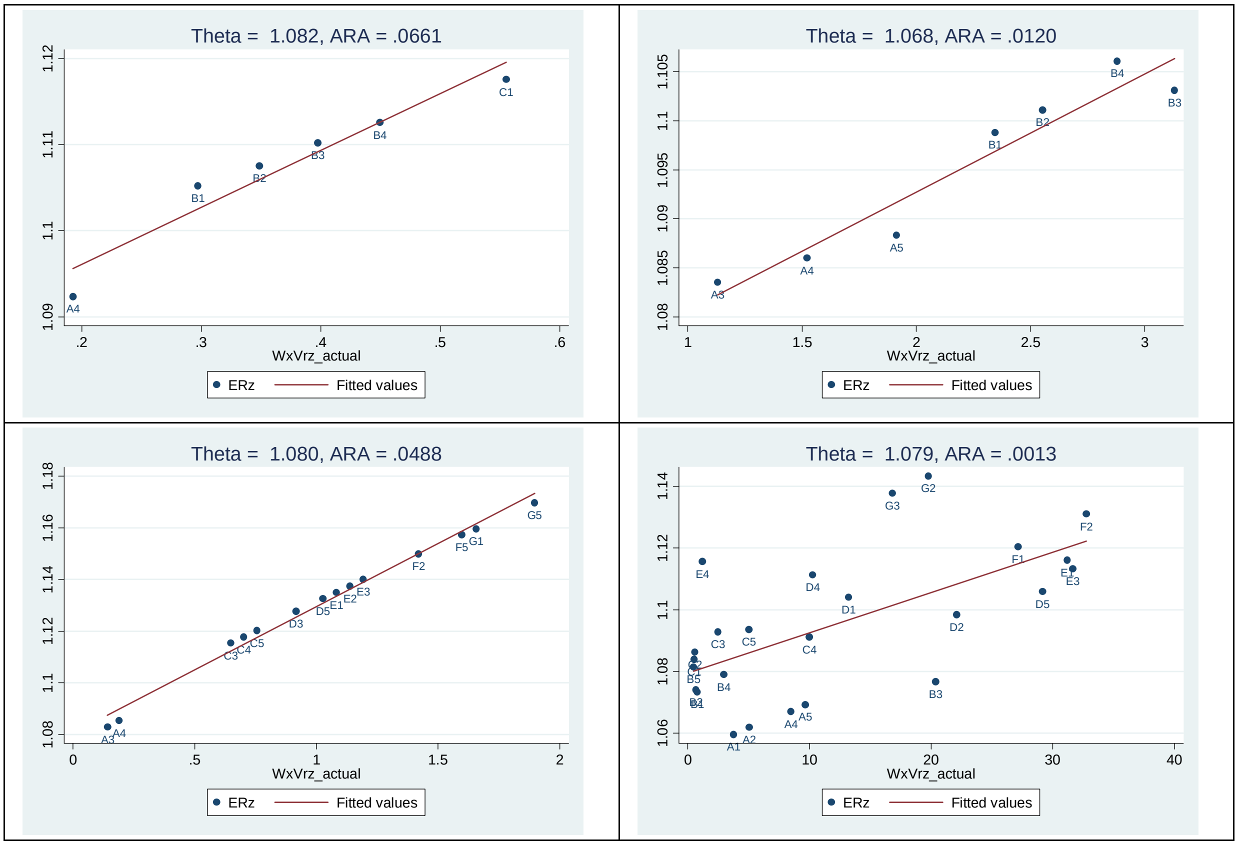
The website provides an optimization tool that suggests the efficient portfolio of loans for the investor's preferred risk return trade-off, under the assumption that loans are uncorrelated with each other and with outside investment opportunity. The risk measure is the variance of the diversified portfolio 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



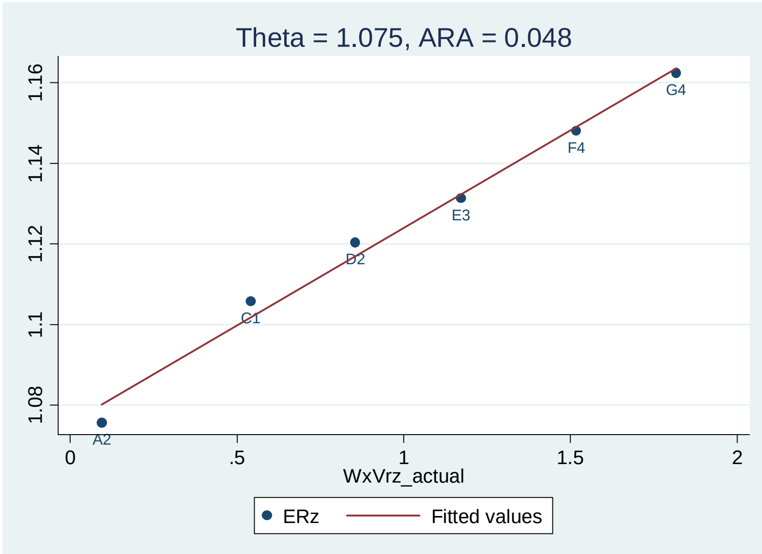
In color: zip codes with Lending Club investors. The color intensity reflects the total dollar amount invested in LC by investors in each zip code.

Figure 2: Geographical Distribution of Lending Club Investors

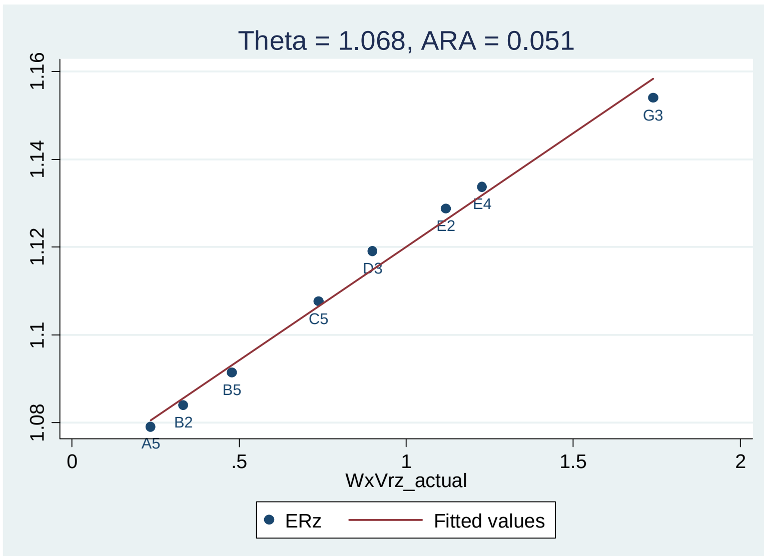


Each plot represents one investment in our sample. The plotted points represent the risk and weighted return of each of the buckets that compose the investment. The dots are labeled with the corresponding risk classification of the bucket. The vertical axis measures the expected return of a risk bucket, 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



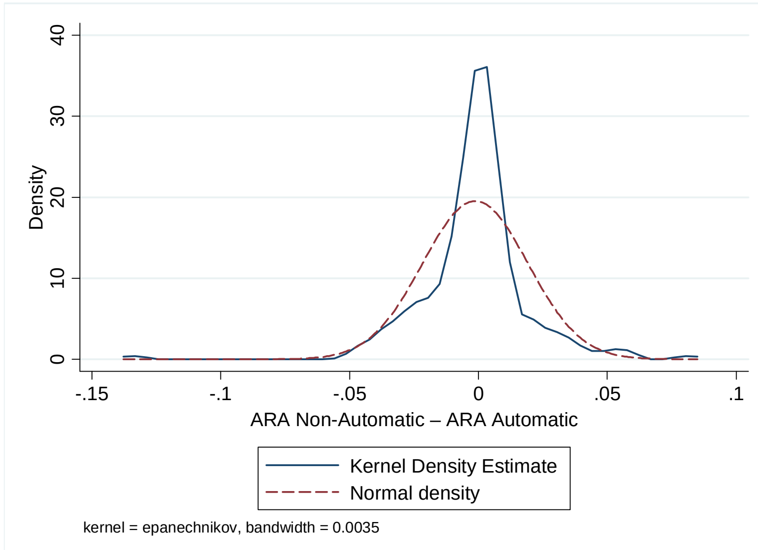
(a) Automatic Buckets



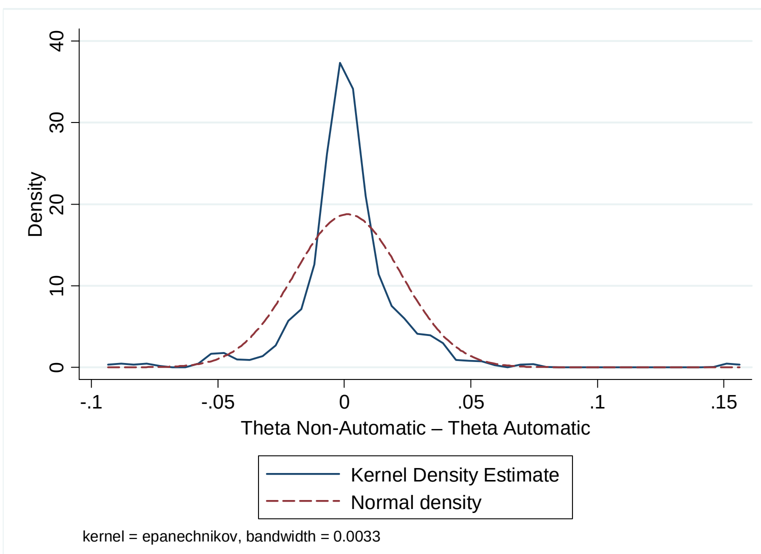
(b) Non-Automatic Buckets

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: Example of Risk Aversion Estimation Using Automatic and Non-Automatic Buckets for the Same Investment



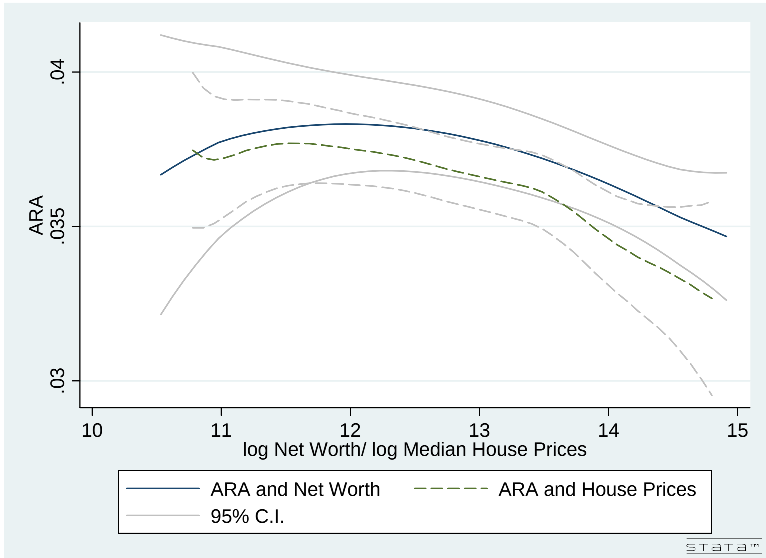
(a) ARA: Automatic and Non-Automatic Choices



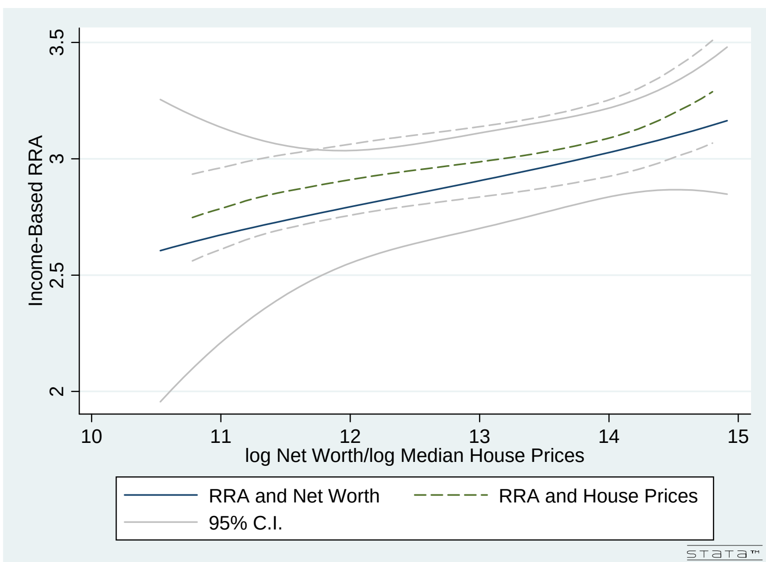
(b) θ: Automatic and Non-Automatic Choices

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

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** (1)			**Diversified investments** (2)			**With real estate data** (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

Variable	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:

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

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

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**	0.022***	0.035***	
	(0.004)	(0.008)	(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***	0.123***	0.203***	
	(0.019)	(0.031)	(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 5: Risk Aversion and Wealth, Cross Section Estimates

Dependent Variable: (in logs)	ARA	Income based RRA	Investment
	(1)	(2)	(3)
A. No Fixed Effects			
log (House Value)	-0.166***	0.192***	0.367***
	(0.047)	(0.048)	(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*	-4.815***	1.290
	(1.521)	(1.611)	(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 6: Risk Aversion and Wealth Shocks, Investor-Specific Estimates