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

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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 obtain risk preference parameters of similar magnitude and heterogeneity across investors than those in experimental studies. Using house prices as an indicator of investor wealth, we find that investors' willingness to take risk in LC is affected by their outside wealth: wealthier investors are more risk averse, but any given investor becomes more risk averse after a negative wealth shock. These wealth elasticities consistently extrapolate to other investor decisions.

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1 Introduction

A large body of empirical literature estimates the parameters that characterize agents' attitudes towards risk and, more generally, the shape of the utility function. Most recent studies rely on estimates from laboratory and field experiments based on individual choices across carefully designed lotteries with pure idiosyncratic risk.[1] To date, validating the experimental results in real life investment choices has been hindered by the difficulty of fully characterizing the risk return trade-offs faced by agents.[2] This has led to the exploration of alternative environments with pure idiosyncratic risk, like race track betting, behavior in game shows, and insurance choices.[3] In these environments, factors external to the choice setting, such as the level and risk of outside wealth, are typically not observable. However, these factors have been shown to affect risk taking behavior in field experiments, and accounting for them is necessary to characterize individual preferences (Harrison, Lau and Towe (2007a)).

In this paper, we analyze the risk taking behavior of 2,168 investors based on their actual financial decisions in a person-to-person lending platform, Lending Club (LC). Specifically, we estimate individual-specific absolute and relative risk aversion parameters (respectively, ARA and RRA) and, using house value as a proxy for investors' wealth, their elasticity to wealth. LC is an online lending platform that allows individuals to invest in diversified portfolios of small loans. This novel environment provides an ideal

[1] See for example Holt and Laury (2002), Choi, Fisman, Gale and Kariv (2007), Harrison, Lau and Rutstrom (2007b), and Tanaka, Camerer and Nguyen (2010).

[2] For example, risk aversion estimates based on portfolio choice between risky and riskless assets (i.e., Blume and Friend (1975a), Blume and Friend (1975b), Cohn, Lewellen, Lease and Schlarbaum (1975), Morin and Suarez (1983), and Guiso and Paiella (2008)) or from the effects of wage changes on labor supply (Chetty (2006)), cannot fully account for the stochastic characteristics of the risky portion, which includes the return to human capital and other unobservable sources of risk.

[3] See for example Jullien and Salanie (2000), Jullien and Salanie (2005), Bombardini and Trebbi (2007), Cohen and Einav (2007), Chiappori, Gandhi, Salanie and Salanie (2008), Chiappori, Gandhi, Salanie and Salanie (2009), Post, van den Assem, Baltussen and Thaler (2008), and Barseghyan, Prince and Teitelbaum (2010).

setting to validate the results from experimental settings as the two share the following key features: the stakes are relatively small (median investment of $375), and investors' portfolio choices can be transformed into choices between well characterized lotteries of pure idiosyncratic risk.

For each portfolio choice we estimate the ARA and the risk premium required to participate in LC. The latter parameter recovers investors' priors about the systematic risk associated with LC. After accounting for the common systematic risk, we transform the investors' portfolio choice into an allocation of funds across loans with pure idiosyncratic default risk. An investor's ARA is obtained from the additional expected return that makes her indifferent between allocating the marginal dollar between two loans with different idiosyncratic default probabilities. The estimation does not rely on a specific form for the utility function. We derive the method using expected utility theory over total wealth and show that it obtains consistent estimates for the curvature of the utility function under alternative common non-expected utility specifications (i.e., loss aversion, narrow framing).

Our estimation procedure does not require any assumption regarding investors' outside wealth. The key identification assumption is that all loans in LC are perceived to have the same systematic risk —i.e., that their returns have the same covariance with the market. The environment allows testing this identification assumption and, more generally, whether differences in investor beliefs about the stochastic properties of LC loans bias parameter estimates. Investors in LC can choose the components of their portfolio manually or through an optimization tool. The tool assumes a common systematic risk across all loans and uses the same information on idiosyncratic loan risk provided to investors. 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.

Risk parameter estimates are of the same order of magnitude than those from experimental studies. 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. We find that wealthier investors exhibit lower ARA and higher RRA (defined over total wealth) when choosing LC loan portfolios. The estimated cross-sectional wealth elasticity of RRA is 0.8. However, investors become more risk averse after experiencing a negative wealth shock. The point estimate of the time-series elasticity ranges between -1.8 and -5.1, indicating that investors' utility function exhibits decreasing relative risk aversion.

The contrasting signs of the cross sectional and investor-specific wealth elasticities highlight why the relationship between risk aversion and wealth for a given investor cannot be obtained solely from cross-sectional data: risk taking behavior in the cross section depends not only on the shape of the utility function but also on the joint distribution of risk aversion and wealth. Most empirical evidence on the shape of risk preferences is based on cross sectional data and implicitly assumes that the distributions of wealth and preferences are independent. A notable exception is Chiappori and Paiella (2008), which attempts to disentangle the two phenomena based on financial portfolio invested in risky assets in a panel of Italian households, and finds the bias from the cross sectional estimation to be economically insignificant. In contrast, the bias would lead to severely underestimate the elasticity of risk aversion to wealth in our setting.

We test whether the estimated level and wealth elasticity of risk aversion 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. The investor-specific ARA is estimated based on the allocation of funds across the loans included in her portfolio. Yet, the median investor has in her portfolio only a subset of the loans available at the time of her investment decision. We show that including the foregone loans 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. We also 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. Namely, when relative risk aversion decreases (increases) in outside wealth, then 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. These implications cannot be tested in the typical experiment, where participants face binary choices, investment amounts are exogenously fixed, and investors' outside wealth is assumed to be constant.

Parallel to field and experimental studies, investors in LC exhibit high levels of risk aversion over small bets that are difficult to reconcile, within the expected utility framework over total wealth, with the observable behavior of agents in environments with larger stakes.[4] We discuss the properties of the utility function that can account for this phenomenon in the LC setting. 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 the investor's portfolio.[5]

[4]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.

[5]This is in line with Barberis and Huang (2001) and Barberis, Huang and Thaler (2006), which propose a framework with loss aversion over changes in specific components of the portfolio, together with concave preferences over entire wealth; and Cox and Sadiraj (2006), which proposes within the expected utility framework, a preference function with two arguments (income and wealth).

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. And Section 7 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] 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

[6]For the latest figures on funded loans and net returns refer to: https://www.lendingclub.com/info/statistics.action.

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

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 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 suggests a minimum variance loan portfolio for the investor's chosen level of idiosyncratic risk (see Figure 1). The tool employs idiosyncratic default probabilities based on credit scores to compute return risk, i.e., the probabilities do not incorporate any correlation with other loans or with outside investment opportunities. Of all fund allocations between LC's inception and June 2009, 39.6% followed the

the classification rule and for an example.

[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.

optimization tool's recommendation with no modification, 47.1% started with a portfolio tool recommendation which was then amended by the investor, and the remaining 13.3% was chosen with no aid of the optimization tool.[9]

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 scheduled payment P_z and the bucket specific default rate p_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, $\Pr(T = \tau) = p_z (1 - p_z)^\tau$ for $T \in [1, 36]$. The resulting expected value and variance of the return of a project in bucket z are:

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

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

[9] We exploit this variation in Subsection 5.3 to validate the identification assumptions.

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 p_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). 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. Person-to-person lending markets, including LC, are not a 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, the investors in LC have special *insights*, which explains why their portfolio departs from just replicating the market.[10]

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 $35 \leq Z$. The resulting portfolio of investor i is

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

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:

$$R_z = \beta_z^i \cdot R_m + r_z \tag{3}$$

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 5.3.[11]

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

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

[10] 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.

[11] 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:

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

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:

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

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.

Assumption 1. *Sharpe's Diagonal Model*[12]

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

The consumer chooses the share of wealth invested in the risk-free asset and $Z + 1$ mutually independent securities. The investor is constrained to non-negative positions in all the LC buckets: $x_z \geq 0$ for $z = 1, ..., 35$.

We begin by considering the expected utility framework over total wealth and then

[12]This assumption may be violated if investors choose loans that provide a better hedge against their outside income fluctuations and such hedging varies across risk buckets. If these two conditions hold our estimates for the risk aversion will be biased. A natural example in our context is hedging associated with geographical location. We find in unreported results (available upon request) that there is no systematic variation across buckets in the geographical distance between borrowers and investors.

discuss the implications of alternative preferences. 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:[13]

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

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

$$E\left[r_z\right] - 1 = \left(-\frac{u''\left(E\left[c^i\right]\right)}{u'\left(E\left[c^i\right]\right)}\right)\cdot W^i x_z^i \cdot var\left[r_z\right]. \tag{4}$$

Note that, even when LC projects are affected by market fluctuations, the optimal investment in bucket z is independent of market risk considerations. This is because the market portfolio holding optimally adjusts to account for the indirect market risk imbedded in LC. 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 in equation (1), and substituting the expectation of the independent return, $E\left[r_z\right]$, with the observable expected return $E\left[R_z\right]$, computed in equation (2), we derive our main empirical equation. Let A^i be the set of all active risk buckets —i.e. $A^i =$

[13]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.

$\{z \leq 35 | x_z^i > 0\}$ −, then for all $z \in A^i$:

$$E[R_z] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \sigma_z^2 \tag{5}$$

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 5.4 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:

$$\theta^i \equiv 1 + \beta_L^i E[R_m] \tag{6}$$

$$ARA^i \equiv -\frac{u''(E[c^i])}{u'(E[c^i])} \tag{7}$$

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 6.4 that this is not the case; information recovered from this first order condition is relevant for understanding investors' overall portfolio choices.

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)):

$$\rho^i \equiv ARA^i \cdot I_L^i \cdot \left(E\left[R_L^i\right] - 1\right) \tag{8}$$

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: 83% are male, 56% are married, and 75% are home owners. The investor demographics are different in all dimensions to those of the respondents of the Survey of Consumer Finances (SCF). The SCF sample has a lower fraction of male respondents (79%), a higher fraction of married respondents (68%), and a lower fraction of home owners (69%). The average investor in our sample is 43 years old, 8 years younger than the average respondent in the SCF. LC investors have an estimated median net worth falling between $250,000 and $499,999, significantly higher than the one of the median U.S. household, estimated at $120,600 by the SCF.

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. 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, panel C, shows the descriptive statistics of median house values on October 2007 in zip codes with and without LC investors. The average median house price of zip codes where LC investors live is $120,000 (32%) higher than in other locations.

4.2 Sample Construction

We consider as a single portfolio choice all the investments an individual makes within a calendar month.[14] The full sample contains 2,168 investors, 5,191 portfolio choices, and 50,254 bucket-specific investments. Table 2, panel A, reports the descriptive statistics of the bucket-specific investments. The median expected return is 12.2%, with a

[14]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 in the empirical analysis.

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

$$E\left[R_z\right] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \sigma_z^2 + \varepsilon_z^i \tag{9}$$

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 (9) 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 (5) 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.[15]

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. However, it is easier to compare the risk aversion exhibited by investors with those of laboratory participants through their income-

[15]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.

based RRA, defined in equation (8), typically reported in experimental studies. Table 3 reports the distribution of expected income and the implied income-based RRA. The mean income-based RRA is 2.85 and its distribution is right-skewed (median 1.62). For comparison, the income-based RRA parameters reported in other experimental work range from 0.3 to 0.52 (see for example Chen and Plott (1998), Goeree, Holt and Palfrey (2002), Goeree, Holt and Palfrey (2003), Goeree and Holt (2004), and Holt and Laury (2002)). Choi et al. (2007) report risk premia with a mean of 0.9, which correspond 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 reconcile, 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 elasticity of the investment amount to changes in wealth.

The parameter θ, defined in equation (6), 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 2.8%), when compared to the variation in the ARA estimates (coefficient of variation of 67%).[16]

[16] 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.

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 Investor Observable Characteristics

The estimated income-based RRA varies according to observable investor characteristics: age, gender, marital status, home ownership status, and investor's zip code median house price. Consistent with previous literature, we find that married and older investors are more risk averse. Moreover, home owners and investors who live in zip codes with higher median house values have larger income-based RRA.[17] This last result is analyzed in more detail in the next subsection.

The risk taking behavior of men and women in our sample displays some differences with respect to the existing experimental studies. Laboratory experiments that typically employ college students as subjects find that women are more risk averse than men.[18] In our sample, the opposite is true: female investors show lower income-based RRA. The difference is most likely due to selection into the LC investor sample. Our estimates are based on relatively young women with an active role in financial decision making, which are potentially different from the median woman in the population.

In an OLS regression of income-based RRA on all investor observable characteristics (available upon request) we find that, except for marital status, the partial correlations between the income-based RRA and investor characteristics have the same sign and significance than the unconditional comparisons described above. The R^2 of the regression is less than 1%, indicating that observable investor characteristics explain only a small

[17]See Table 4.

[18]See Eckel and Grossman (2008) for a survey of the existing evidence.

fraction of the heterogeneity in attitudes towards risk in our sample.

5.3 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 different 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 variation in θ. 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' 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 (5) 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 $B_\beta \equiv \left(\beta_z^i - \beta_L^i\right) / \left(W^i x_z^i \sigma_z^2 / n_z^i\right)$.

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 and expected returns of each bucket. Second, LC's optimization tool employs these idiosyncratic default probabilities to compute bucket risk and return, and it constructs the optimal portfolio under the assumption that all buckets have the same systematic component, i.e. $\beta_z = \beta_L$.[19] Thus, we can use the risk preferences implied by investor choices made through the optimization tool as a benchmark to compare to the risk preferences implied by investment 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 LCs assumptions. It suffices that the difference in beliefs does not vary systematically across buckets. Note, moreover, that our test is based on investors' beliefs at the time of making the portfolio choices. These beliefs need not to be correct ex post.

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

We perform the independent estimation above for all portfolio choices that have at least two Automatic and two Non-Automatic buckets. To verify that investments that

[19] See Appendix B for the derivation of the portfolio suggested by the optimization tool.

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 chose manually. The median ARA is 0.0440 and 0.0441 respectively, and the mean difference across the two groups is not statistically significant at the standard levels. This suggests that our focus in this subsection on investments with an Automatic component is representative of the entire investment sample.

Table 5, panel A, reports the descriptive statistics of the 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 5, columns 1 and 2), and the means are statistically indistinguishable at the 1% level. 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).

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 5, panels B and C, we show that the difference in the distribution of the estimated ARA from the automatic and non-automatic buckets is insignificant both during the first and second half of the sample period. This finding is key for interpreting the results in the next section, where we explore how the risk aversion estimates change in the time series with changes in housing prices. There, we interpret any observed time variation in the ARA estimates as a change in investor risk preferences over time.[20]

Table 5, columns 4 through 6, show that the estimated risk premia, θ, also exhibit almost identical mean and standard deviations when obtained independently using the Automatic and Non-Automatic investment components. The mean difference is not statistically difference at the 1% confidence level. This suggests that our estimates of the risk premium are unbiased.[21]

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 5 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 5 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.

5.4 Consistency Test: Foregone Risk Buckets

In this subsection we test the internal consistency of the investors' portfolio choices within LC. We compare the risk and return of the buckets in the investor's portfolio to those she did not choose (*foregone* buckets) to verify whether the investor's choice is optimal, i.e., that including the foregone risk buckets in the portfolio would lower her utility, given her

[20]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.

[21]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 (5). The intuition is that, for any given return, condition (5) 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.

estimated preferences.

The median investor in the analysis sample assigns funds to 10 out of 35 risk buckets (see Table 2, panel B). Our empirical specification (9) 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 (5), 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:

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

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 (9). 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 (9). 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.

6 Risk Aversion and Wealth

This section explores the relationship between risk taking behavior and investors' outside wealth. First, we find that risk preferences within LC are not independent from investors' wealth and are affected by changes in the value of the investors' outside portfolio. We find that wealthier investors exhibit higher wealth-based RRA when choosing their portfolio of loans within LC. Moreover, the investor specific RRA increases after they experience a negative wealth shock.

A natural question concerning risk taking behavior in small stake environments, is whether these preferences are related to investors' preferences in broader contexts. We find evidence in support of this hypothesis; investors found to be more risk averse when choosing their LC portfolio, are also more risk averse when choosing how much to invest in LC relative to other investment opportunities. Furthermore, wealth shocks affect investors' specific risk preferences in the same qualitative way when choosing their LC portfolio as when they choose how much to invest in the program.

Although wealth-based RRA ($RRA^i = ARA^i W^i$) is not directly observable, we compute its elasticity with respect to wealth, $\xi_{RRA,W}$, based on our estimates of ARA and income-based RRA. We use the following relationships, which are derived from the definition of the wealth-based RRA and income-based RRA in equation (8):

$$\xi_{RRA,W} = \xi_{\rho,W} - (\xi_{I_L,W} - 1) \tag{10}$$

$$= \xi_{ARA,W} + 1, \tag{11}$$

where $\xi_{\rho,W}, \xi_{ARA,W}$, and $\xi_{I_L,W}$ refer to the wealth elasticities of the income-based RRA, ARA, and total investment in LC, respectively.

Estimates of these elasticities in the cross section of investors reflect the shape of the utility function only under the assumption that wealth and risk preferences are independently distributed in the population. Instead of relying on that assumption, we exploit the panel dimension of our data to estimate an investor-specific elasticity from the change in risk preferences after a wealth shock. The comparison of the cross sectional and investor-specific elasticities allows us to characterize, both, the joint distribution of risk aversion and wealth in the population of LC investors, and the shape of the utility function.

Equations (10) and (11) provide us with two separate ways of estimating the cross-sectional and investor specific elasticities of the wealth-based RRA. We find that the corresponding estimates consistently lead to the same conclusions: RRA and wealth are positively correlated across investors in LC, but investors exhibit substantial decreasing relative risk aversion.

6.1 House Price Changes as a Proxy for Wealth Shocks

We use the median house price in the investor's zip code as an indicator of wealth when comparing risk aversion across investors. And we exploit the drop in the value of houses during our sample period to analyze the effect of a negative wealth shock on the investor's attitude towards risk. The main advantage of using house prices as a proxy for wealth is that they vary substantially across zip codes and over time during the sample period. The average house price declines 28.8% between October 2007 and April 2008. In addition, the time series house price variation is heterogeneous across investors: the median house price decline is 20.1%. Table 6 shows the time series evolution of the distribution of house prices in the LC zip codes.

Since investor wealth is unobservable, our estimates are obtained from the reduced form relationship between risk aversion and house prices. As long as, on average, wealthier investors live in zip codes with higher median house prices, our wealth proxy will provide the relevant sign of the cross sectional distribution of risk preferences. And, as long as investor wealth changes are, on average, positively correlated with changes in house prices in the time series, our proxy will also provide the relevant sign for the within investor ARA elasticity to wealth. Both assumptions seem reasonable in the context of our analysis and imply that the reduced form estimates allow us to gauge the sign of the elasticity of risk aversion to wealth.

House prices are a noisy proxy for wealth, and thus the absolute magnitude of the reduced form estimates is difficult to interpret. The measurement error in our wealth proxy is likely to be strongly correlated with fixed investor characteristics. For example, our proxy overstates housing wealth for investors with higher mortgage debt, and understates it for investors with larger financial assets holdings. Our within investor analysis, which compares changes in the investment behavior of the same investor before and after a drop in house prices, controls for all time invariant investor characteristics and thus accounts for these sources of measurement error.

Zip code housing prices exhibit a strong positive correlation with imputed investor's net worth as of October 2007, obtained from Acxiom. The correlation is significantly larger for home owners (0.417) than for renters (0.261) in our sample. Thus, our preferred estimates of the relationship between investor risk taking behavior and wealth are obtained from the subsample of home owners.

6.2 Cross-Sectional Evidence

We begin by exploring non-parametrically the relationship between the risk aversion estimates and our wealth measure for the cross section of all investors in our sample. Figure 6 plots a kernel-weighted local polynomial smoothing of the risk aversion measure. The horizontal axis measures the (log) median house price in the investor's zip code at the time of the portfolio choice. Absolute risk aversion is decreasing in our wealth proxy, while income-based relative risk aversion is increasing.

Figure 6 also illustrates this relationship for home owners and renters separately. As mentioned above, the measurement error of our wealth proxy is likely to be smaller for home owners. If the measurement error distribution is independent of risk aversion, the cross sectional elasticity of risk aversion to our wealth proxy illustrated in Figure 6 should be biased towards zero for renters. This is consistent with the patterns observed in Figure 6: the relationship of both ARA and the income-based RRA with the wealth proxy is flatter for renters than for home owners. For this reason, all the parametric estimations below are performed on the subsample of home owners only.

Turning to parametric evidence, we estimate the cross sectional elasticity of risk aversion to wealth using the following pooled OLS regression:[22]

$$\ln(RiskAversion_{it}) = \beta_0 + \beta_1 \ln(HouseValue_{it}) + \omega_{it}. \tag{12}$$

The left hand side variable is the (log) measure of risk aversion obtained for investor i for

[22] The parameter estimates from the pooled OLS are qualitatively similar to those obtained by estimating OLS on the cross section of investor average outcomes.

a portfolio choice at month t.

Table 7, panel A (column 1) shows the estimated cross sectional elasticity β_1 for ARA. The estimate is statistically significant at the 1% confidence level and confirms the non-parametric relationships: wealthier investors exhibit lower ARA. Column 2 shows that the income-based RRA increases in wealth. The magnitude of this cross sectional elasticity does not appear to be economically significant. The estimate of $\beta_1 = 0.19$ implies that an investor who lives in a zip code with house prices one standard deviation above the mean (i.e., 28.8% higher house price) has an income-based RRA of 3 instead of the overall mean of 2.85.

The first row of Table 8 shows the cross-sectional wealth elasticity of the wealth-based RRA. Column 1 shows the computations based on our estimated ARA and equation (11). Column 2 shows the computations based on our estimates of the income-based RRA and equation (10). Both estimates consistently suggest that the wealth-based RRA is larger for wealthier investors: the cross sectional elasticity ranges between 0.834 and 0.824.

6.3 Within-Investor Estimates

The above elasticity, obtained from the variation of risk preferences 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 risk aversion in the population are independent.[23] To identify the functional form of individual risk preferences we estimate the risk aversion elasticity using within-investor time series variation. The within-investor elasticity is estimated from specification (12),

[23] 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.

augmented with investor specific dummies as controls (investor fixed effects):

$$\ln\left(RiskAversion_{it}\right) = \alpha_i + \beta_2 \ln\left(HouseValue_{it}\right) + \omega_{it}. \tag{13}$$

The elasticity β_2 is estimated from the sensitivity of risk aversion to changes in the wealth proxy for each investor. Specification (13) accounts for all cross sectional differences in risk aversion levels with investor fixed effects.

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 (13) comes from less than half of the original sample. For this reason, 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). This suggests the within-investor results below are representative for the full investor sample.

Table 7, panel B, reports the estimated wealth elasticities of ARA and the income-based relative risk aversion. 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 $\beta_2 = -4.18$ indicates that the average investor's income-based RRA increases from 2.85 to 4.0 when she experiences a 10% decline in house prices in her zip code.

The second row of Table 8 shows the wealth elasticity of the investor specific wealth-based RRA in the time series. Column 1 shows the computations based on our estimated

ARA and equation (11). Column 2 shows the computations based on our estimates of the income-based RRA and equation (10). Both estimates consistently suggest that investors exhibit decreasing wealth-based RRA, with an elasticity that ranges between -1.82 and -5.10, although the first of these estimates is not statistically different from zero.

6.4 External Validity: Amount Invested 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 outside wealth, then the share of wealth invested in LC will increase (decrease) in outside 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 (12) and (13) using the (log) amount invested in LC. Table 7 reports the estimated cross sectional and within investor elasticities.

We find that the investment amount is increasing with investor house values in the cross section (Table 7, panel A, 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 wealth-based RRA cross sectional elasticities reported in Tables 7 and 8. 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.

Note that the estimated wealth elasticity of total investment in LC is positive and grater than one when we add investor fixed effects (Table 7, panel B, 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.

7 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.

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. 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.

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 et al. (2006), which propose a framework where agents exhibit loss aversion over changes in specific components of their overall portfolio, together with decreasing relative risk aversion over their entire wealth. In the expected utility framework, Cox and Sadiraj (2006) propose a utility function with two arguments (income and wealth) where risk aversion is defined over income, but it is sensitive to the overall wealth level. We leave the exploration of these alternatives in the LC environment for future research.

References

Arellano, Manuel, and Stephane Bonhomme (2009) 'Identifying distributional characteristics in random coefficients panel data models.' *Working Paper*

Barberis, Nicholas, and Ming Huang (2001) 'Mental accounting, loss aversion, and individual stock returns.' *The Journal of Finance* 56(4), 1247–1292

Barberis, Nicholas, Ming Huang, and Richard H. Thaler (2006) 'Individual preferences, monetary gambles, and stock market participation: A case for narrow framing.' *The American Economic Review* 96(4), 1069–1090

Barseghyan, Levon, Jeffrey Prince, and Joshua Teitelbaum (2010) 'Are risk preferences stable across contexts? evidence from insurance data.' *The American Economic Review*

Blume, Marshall, and Irwin Friend (1975a) 'The asset structure of individual portfolios and some implications for utility functions.' *The Journal of Finance* 30(2), 585–603

____ (1975b) 'The demand for risky assets.' *The American Economic Review* 65(5), 900–922

Bombardini, Matilde, and Francesco Trebbi (2007) 'Risk aversion and expected utility theory: an experiment with large and small stakes.' *Working Paper*

Chen, Kay Yut, and Charles Plott (1998) 'Non-linear behavior in sealed bid first price auctions.' *Games and Economic Behavior* 25(1), 34–78

Chetty, Raj (2006) 'A new method of estimating risk aversion.' *The American Economic Review* 96(5), 1821–1834

Chiappori, Pierre-Andre, Amit Gandhi, Bernard Salanie, and Francois Salanie (2008) 'You are what you bet: Eliciting risk attitudes from horse races.' *Working Paper*

____ (2009) 'Identifying preferences under risk from discrete choices.' *American Economic Review* 99(2), 356 – 362

Chiappori, Pierre-Andre, and Monica Paiella (2008) 'Risk aversion is constant: Evidence from panel data.' *Working Paper*

Choi, Syngjoo, Raymond Fisman, Douglas Gale, and Shachar Kariv (2007) 'Consistency and heterogeneity of individual behavior under uncertainty.' *The American Economic Review* 97(5), 1921–1938

Cohen, Alma, and Liran Einav (2007) 'Estimating risk preferences from deductible choice.' *The American Economic Review* 97(3), 745–788

Cohn, Richard A., Wilbur G. Lewellen, Ronald C. Lease, and Gary G. Schlarbaum (1975) 'Individual investor risk aversion and investment portfolio composition.' *The Journal of Finance* 30(2), 605–620

Cox, James, and Vjollca Sadiraj (2006) 'Small- and large-stakes risk aversion: Implications of concavity calibration for decision theory.' *Games and Economic Behavior* 56, 45–60

Eckel, Catherine, and Philip Grossman (2008) 'Differences in the economic decisions of men and women: Experimental evidence.' In *Handbook of Experimental Economics Results,* ed. Charles Plott and Vernon Smith (New York: Elsevier) pp. 509–519

Goeree, Jacob, and Charles Holt (2004) 'A model of noisy introspection.' *Games and Economic Behavior* 46(2), 365–382

Goeree, Jacob, Charles Holt, and Thomas Palfrey (2002) 'Quantal response equilibrium and overbidding in private-value auctions.' *Journal of Economic Theory* 104(1), 247–272

——— (2003) 'Risk averse behavior in generalized matching pennies games.' *Games and Economic Behavior* 45(1), 97–113

Guiso, Luigi, and Monica Paiella (2008) 'Risk aversion, wealth, and background risk.' *Working Paper*

Harrison, Glenn, Morten Lau, and Charles Towe (2007a) 'Naturally occurring preferences and exogenous laboratory experiments: A case study of risk aversion.' *Econometrica* 75(2), 433–458

Harrison, Glenn, Morten Lau, and Elisabet Rutstrom (2007b) 'Estimating risk attitudes in denmark: A field experiment.' *Scandinavian Journal of Economics* 109(2), 341–368

Holt, Charles A., and Susan K. Laury (2002) 'Risk aversion and incentive effects.' *The American Economic Review* 92(5), 1644–1655

Jullien, Bruno, and Bernard Salanie (2000) 'Estimating preferences under risk: The case of racetrack bettors.' *The Journal of Political Economy* 108(3), 503–530

——— (2005) 'Empirical evidence on the preferences of racetrack bettors.' In *Efficiencies of Sports and Lottery Markets,* ed. Haush Ziemba pp. 1–21

Morin, Roger-A., and A. Fernandez Suarez (1983) 'Risk aversion revisited.' *The Journal of Finance* 38(4), 1201–1216

Post, Thierry, Martijn J. van den Assem, Guido Baltussen, and Richard H. Thaler (2008) 'Deal or no deal? decision making under risk in a large-payoff game show.' *American Economic Review* 98(1), 38–71

Rabin, Matthew (2000) ‘Risk aversion and expected-utility thoery: A calibration theorem.’ *Econometrica* 68(5), 1281–1292

Rabin, Matthew, and Richard Thaler (2001) ‘Anomalies: Risk aversion.’ *The Journal of Economic Perspectives* 15(1), 219–232

——— (2002) ‘Response from matthew rabin and richard h. thaler.’ *The Journal of Economic Perspectives* 16(2), 229–230

Rubinstein, Ariel (2001) ‘Comments on the risk and time preferences in economics’

Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen (2010) ‘Risk and time preferences: Linking experimental and household survey data from vietnam.’ *American Economic Review* 100(1), 557–571

Treynor, Jack, and Fischer Black (1973) ‘How to use security analysis to improve portfolio selection.’ *Journal of Business* 46(1), 66–86

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*:

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

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 (3) 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 (4):

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

$\left(E\left[r_L\right] - 1\right)/var\left[r_L\right]$ 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 (9) 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 (5) 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 5). 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 (5): $R_L = \sum_{z=1}^{Z_L} \widetilde{x}_z R_z$ 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 (3), 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:

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

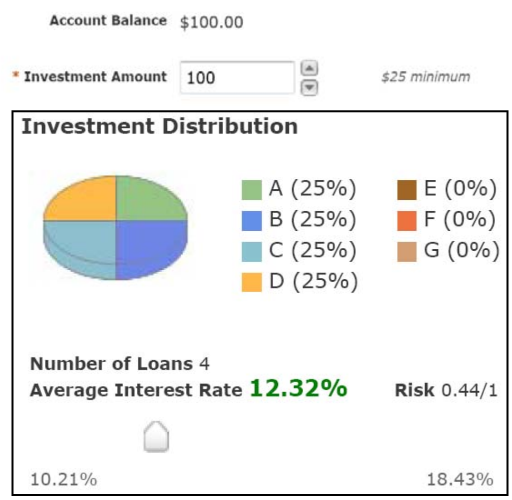
ARA and RRA refer to absolute and wealth-based relative risk aversion: $ARA \equiv -\frac{u''\left(E\left[c^i\right]\right)}{u'\left(E\left[c^i\right]\right)}$ and $RRA \equiv -\frac{u''\left(E\left[c^i\right]\right)}{u'\left(E\left[c^i\right]\right)}W$. We obtain the following testable implications:

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.*

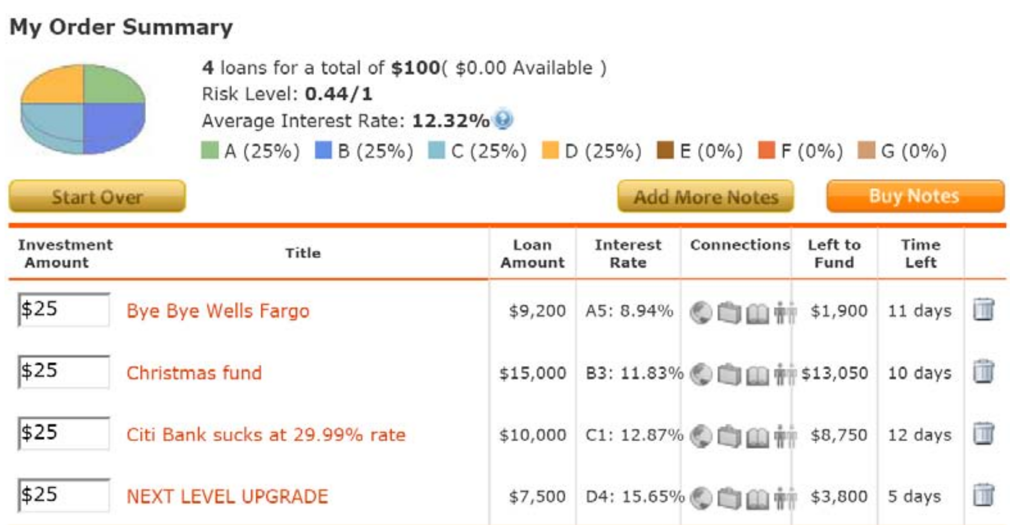
Result 2. *If the wealth-based RRA decreases (increases) in outside wealth, then the share of wealth invested in LC, I_L/W, increases (decreases) in outside wealth.*

We test these implications by estimating specifications (12) and (13) using the (log) amount invested in LC.

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

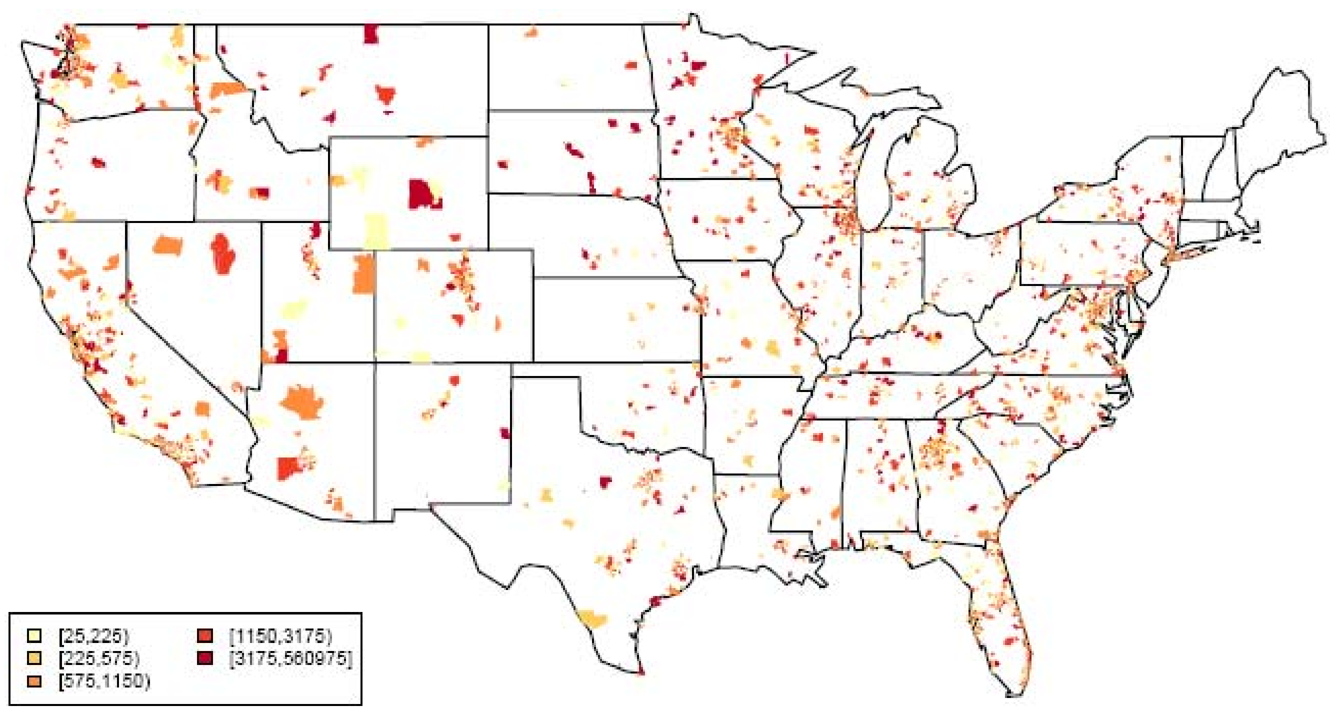


B. Screen 2: Suggested Portfolio Summary



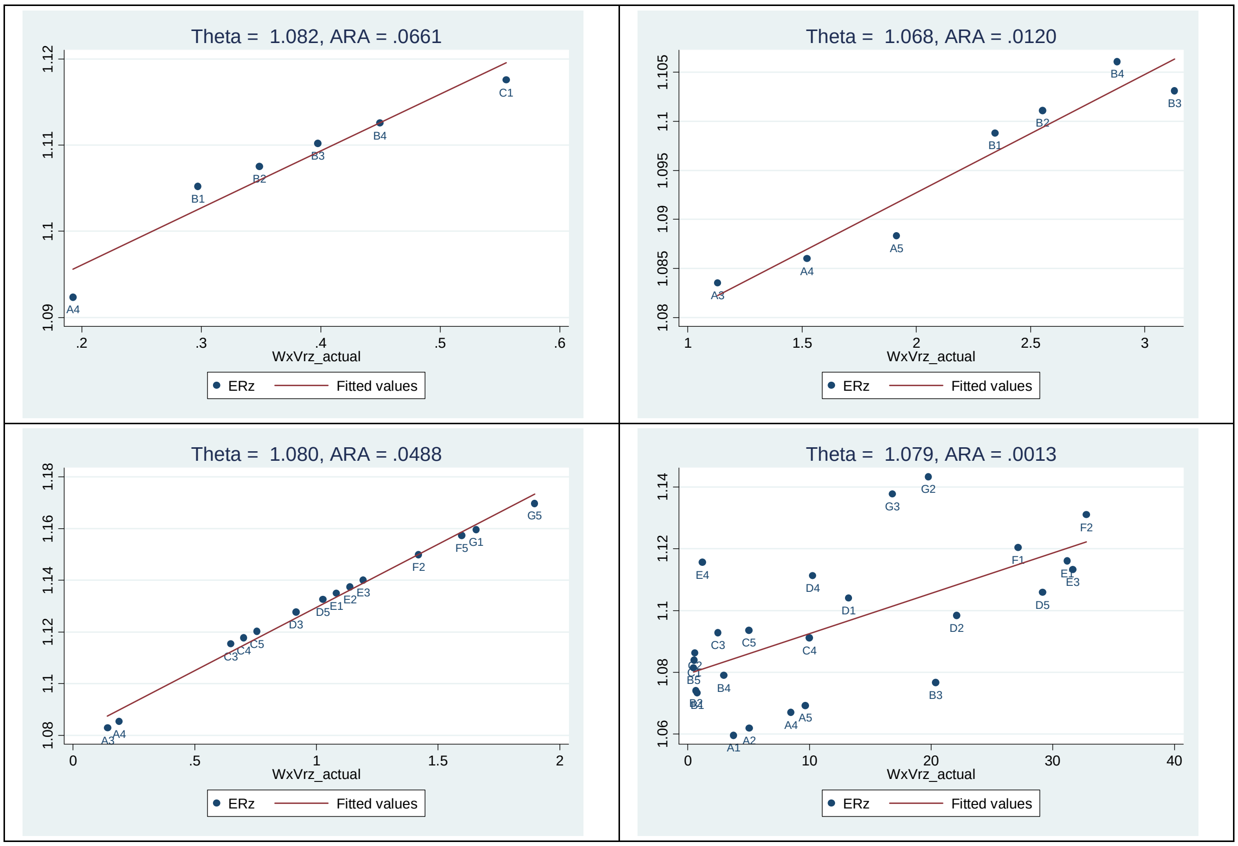
The website provides an optimization tool that suggests the efficient portfolio of loans for the investor's preferred risk return trade-off, under the assumption that loans are uncorrelated with each other and with outside investment opportunity. The risk measure is the variance of the diversified portfolio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

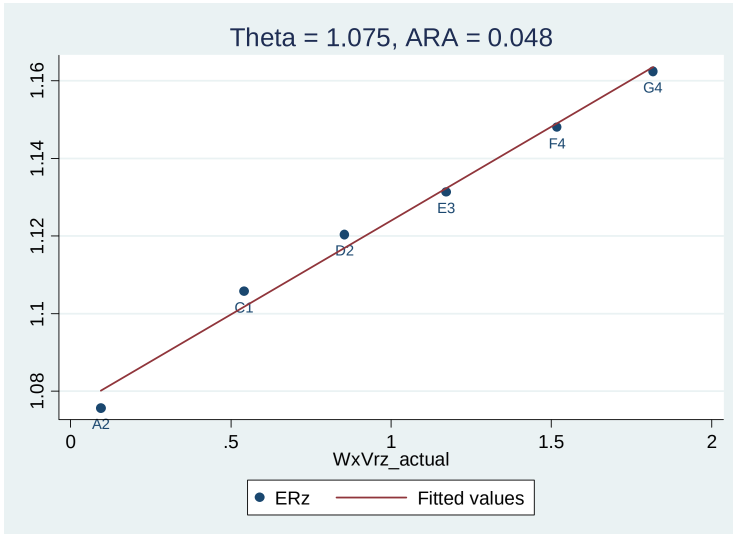
Figure 2: Geographical Distribution of Lending Club Investors



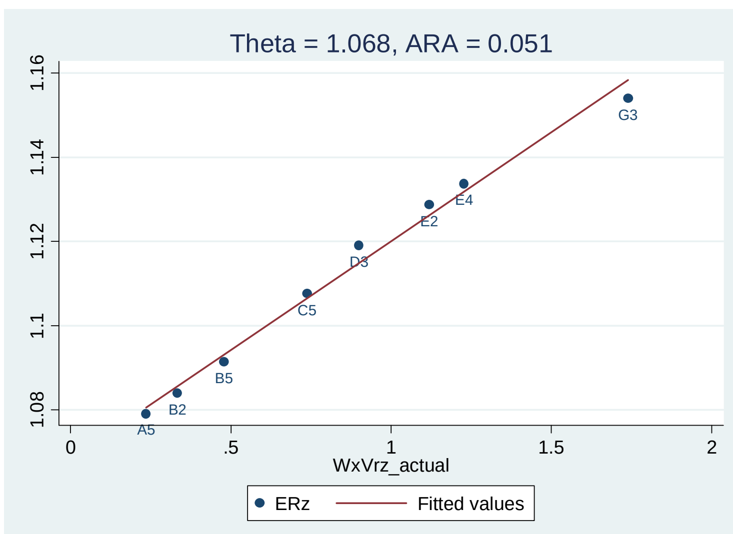
Each plot represents one investment in our sample. The plotted points represent the risk and weighted return of each of the buckets that compose the investment. The dots are labeled with the corresponding risk classification of the bucket. The vertical axis measures the expected return of a risk bucket,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



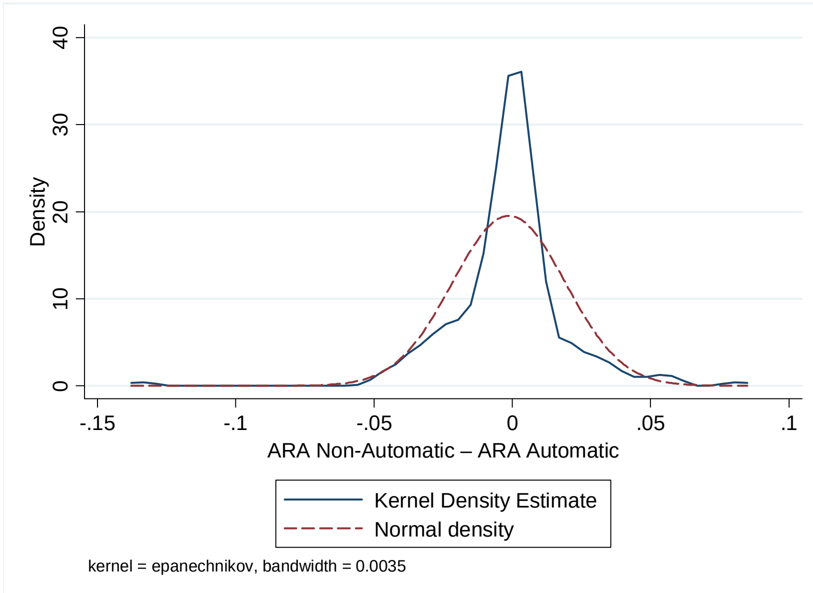
B. Non-Automatic Buckets



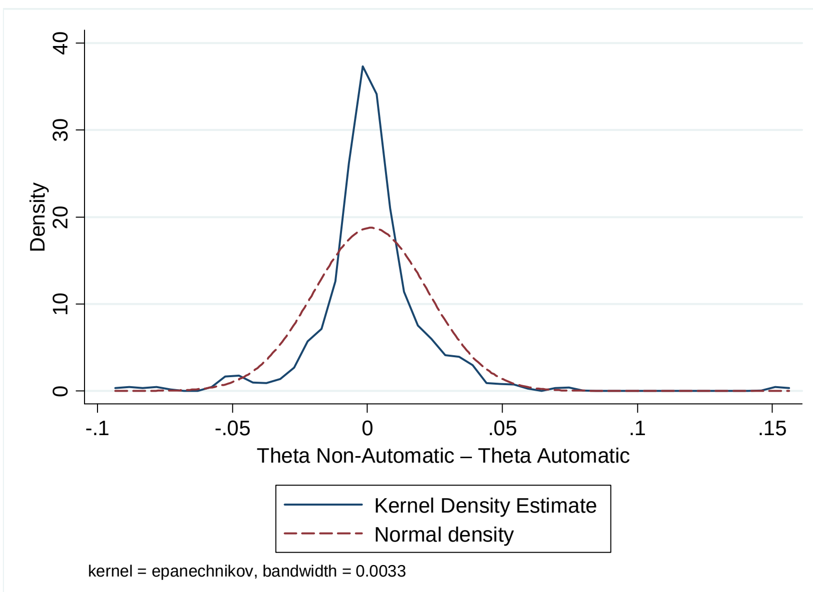
Both plots represent allocations to risk buckets of the same actual investment. As in Figure 3, the plotted points represent the risk and weighted return of each of the buckets that compose the investment. Panel A shows the buckets that were chosen by the portfolio tool (*Automatic*), and panel B shows 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* Non-Automatic – *ARA* Automatic



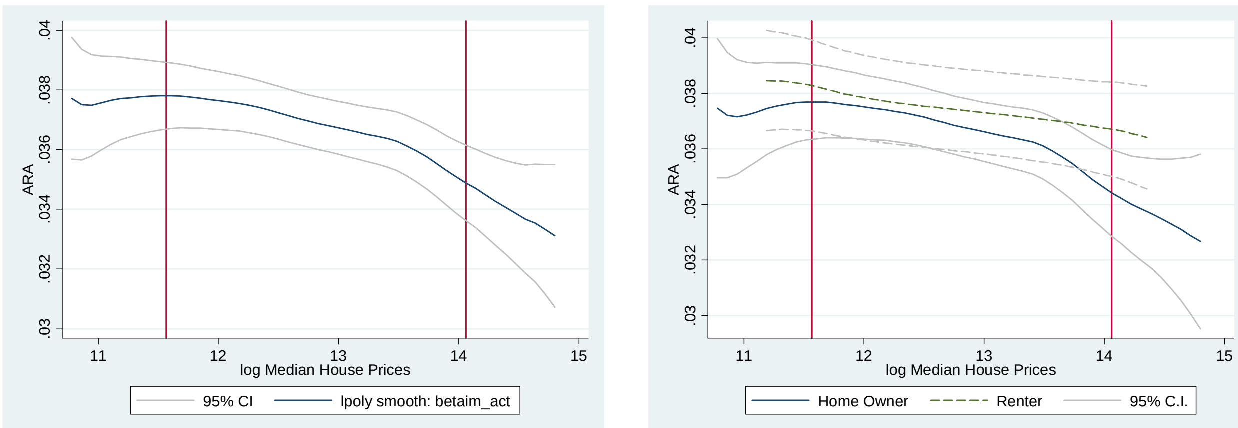
B. θ_0 Non-Automatic – θ_0 Automatic



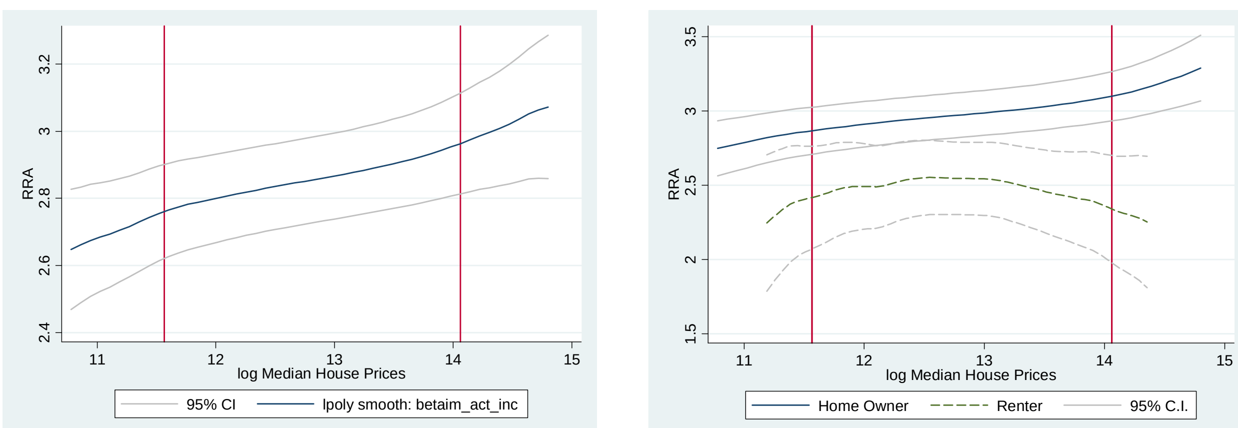
Difference between the estimate for ARA and θ obtained using buckets chosen directly by investors (*Automatic*) and buckets suggested by optimization tool (*Non-Automatic*), for the same investment.

Figure 5: Distribution of the Difference in ARA and θ Estimates Obtained from Automatic and Non-Automatic Buckets for the Same Investment

A. Absolute Risk Aversion



B. Relative Risk Aversion



The vertical axis plots a weighted local polynomial (degree zero) 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) median house price at the investor's zip code at the time of the portfolio choice, our proxy 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%
C. Median Zip Code House Values			
LendingClub Investor zip codes	374.9	301.4	266.2
Other zip codes	254.9	200.6	202.6

Sources: Lending Club 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 reported in panel B 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, and home ownership status. We use investor zip codes to match the LC data with real estate price data to construct the statistics in panel C. We use the Zillow Home Value Index as a proxy for house values in a zip code. The Zillow Index for a given geographical area is the median property value in that area.

Table 1: Borrower, Investor, and Investor Zip Code House Price Characteristics

Sample/Subsample:	All Investments			At least 2 buckets Diversified investments			With real estate data		
	(1)			(2)			(3)		
	Mean	S.D	Median	Mean	S.D	Median	Mean	S.D	Median
A. Unit of observation: investor-bucket-month									
	(N = 50,254)			(N = 43,662)			(N = 37,248)		
Investment ($)	302.8	2,251.4	50.0	86.0	206.9	50.0	90.1	220.5	50.0
N Projects in Bucket	1.9	1.8	1.0	2.0	1.8	1.0	2.0	1.8	1.0
Interest Rate	12.89%	2.98%	12.92%	12.91%	2.96%	12.92%	12.92%	2.97%	12.92%
Default Rate	2.77%	1.45%	2.69%	2.78%	1.45%	2.84%	2.79%	1.45%	2.84%
E(PV $1 investment)	1.122	0.027	1.122	1.122	0.027	1.123	1.122	0.027	1.123
Var(PV $1 investment)	0.036	0.020	0.035	0.027	0.020	0.022	0.036	0.020	0.035
B. Unit of observation: investor-month									
	(N = 5,191)			(N = 3,745)			(N = 3,145)		
Investment	2,932	28,402	375	1,003	2,736	375	1,067	2,934	400
N Buckets	9.7	8.7	7.0	11.7	8.4	10.0	11.8	8.5	10.0
N Projects	18.8	28.0	8.0	23.3	28.9	14.0	23.8	29.5	14.0
E(PV $1 investment)	1.121	0.023	1.121	1.121	0.021	1.121	1.121	0.021	1.121
Var(PV $1 investment)	0.0122	0.0159	0.0054	0.0052	0.0065	0.0025	0.0066	0.0070	0.0038
Zip Code Median House Price	407,566	300,482	307,106	413,626	296,276	315,214	413,626	296,276	315,214
% Investment/House Value	0.47%	2.46%	0.11%	0.34%	0.86%	0.11%	0.34%	0.86%	0.11%

Each observation in panel A represents an investment allocation 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. Median house price of the zip code where the investor is located is obtained from the Zillow Home Value Index. Investment/House Value is calculated using the median house price as a proxy for house value. 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
p5	0.00407	1.055	5.89	0.20
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
p95	0.06179	1.119	475.8	10.25
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 investment 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

	Gender		Age		Marital Status		Home Ownership		Zip Code House Values	
	Female	**Male**	**<42**	**>42**	**Single**	**Married**	**Renter**	**Owner**	**<median**	**>median**
Mean	2.54	2.92	2.62	3.05	2.74	2.93	2.44	2.97	2.68	3.03
sd	3.14	3.71	3.47	3.74	3.47	3.73	3.12	3.76	3.50	3.75
Δ	**0.38****		**0.43*****		**0.19***		**0.53*****		**0.35*****	
p1	-0.12	-0.17	-0.17	-0.15	-0.07	-0.19	-0.15	-0.16	-0.15	-0.17
p5	0.25	0.20	0.19	0.22	0.22	0.20	0.19	0.21	0.20	0.20
p25	0.51	0.57	0.52	0.60	0.54	0.57	0.53	0.57	0.50	0.66
p50	1.50	1.65	1.43	1.73	1.56	1.66	1.35	1.69	1.41	1.74
p75	3.51	3.73	3.14	4.12	3.48	3.79	2.93	3.89	3.42	3.88
p95	8.71	10.58	9.93	10.87	10.03	10.67	8.77	10.70	9.95	10.67
p99	13.79	17.81	16.74	17.81	16.42	18.26	14.87	18.26	16.74	17.81
N	486	2,488	1,484	1,661	1,353	1,792	746	2,399	1,669	1,476

Income-Based Relative Risk Aversion obtained as in Table 3. The mean difference across each pair of groups is reported. *, **, and *** indicate that the difference is significant at the 10%, 5%, and 1% levels of confidence, respectively. pN represents the N^{th} percentile of the distribution.

Table 4: Income-Based RRA by Observable Investor Characteristics

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 5: Estimates from Automatic and Non-Automatic Buckets for the same Investment

Variable	Mean	Std. Dev.	Distribution Percentile				
			1%	25%	50%	75%	99%
2007m10	529,569	377,676	93,564	226,627	373,490	828,332	1,672,757
2007m11	493,379	350,041	77,140	233,987	356,339	688,168	1,680,504
2007m12	432,827	297,152	90,029	220,292	337,619	602,994	1,488,051
2008m1	436,203	317,732	77,777	212,546	340,518	560,174	1,577,157
2008m2	410,875	300,604	88,371	198,949	301,302	530,068	1,495,770
2008m3	383,657	270,396	80,448	200,511	305,075	489,366	1,499,999
2008m4	377,165	241,504	86,147	202,500	298,592	469,605	1,221,598
Total % Decline	28.8%		7.9%	10.6%	20.1%	43.3%	27.0%

Descriptive statistics of the median zip code house price where Lending Club investors are located, by month. The bottom row shows the percentage decline of each statistic between October 2007 and April 2004.

Table 6: Time Series of House Price Distribution during Sample Period

Dependent Variable: (in logs)	ARA (1)	Income based RRA (2)	Investment (3)
A. Cross Section			
log (House Value)	-0.166***	0.192***	0.367***
	(0.047)	(0.048)	(0.070)
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)
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 elasticity of risk aversion to wealth in the cross section (panel A) and investor-specific (panel B). 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 variable is the (log) median house price in the investor's zip code in time t (and an investor fixed effect in the even numbered columns). Standard errors are heteroskedasticity robust and clustered at the zip code level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

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

Wealth elasticity of the RRA (wealth-based)	$\xi_{RRA,W} =$ $\xi_{ARA,W} + 1$ (1)	$\xi_{\rho,W} - (\xi_{I,W} - 1)$ (2)
Cross Section Elasticity	0.834	0.824
	(0.047)	(0.047)
Investor-Specific Elasticity	-1.825	-5.104
	(1.521)	(1.611)

Elasticity of the (wealth-based) relative risk aversion to the cross sectional and investor-specific variation in wealth. Calculated using relationships (11) and (10) in the text (columns 1 and 2, respectively), and based on the estimated wealth elasticities of the absolute risk aversion, income-based relative risk aversion, and investment in Lending Club from Table 7. The standard errors in column 2 are obtained from the linear combination of the parameters of a seemingly unrelated regression estimation of the models in columns 2 and 3 of Table 7. The standard errors are heteroskedasticity robust and clustered at the zip code level.

Table 8: Calculated Wealth Elasticity of RRA (wealth-based)