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

Daniel Paravisini Veronica Rappoport Enrichetta Ravina

Columbia Business School

17th November 2009

Abstract

We estimate risk aversion from the actual financial decisions of a sample of 2,168 U.S. investors participating in a person-to-person lending platform. We find a large degree of heterogeneity in the relative risk aversion (RRA) parameter, with an average of 2.85, and a median of 1.62. We exploit the panel dimension of the data to estimate independently the correlation between risk aversion and wealth in the cross section of investors, and the elasticity of risk aversion with respect to changes in wealth for a given investor. Using house prices as an indicator of investor wealth, we find a positive although economically small, correlation between relative risk aversion and wealth in the cross section. In contrast, when we employ investors fixed effect to estimate the within-person elasticity, we find that it is negative and substantial (-4.2). Our estimation procedure allows us to test rationality and the consistency of investor behavior.

*We are grateful to Lending Club for providing the data and for helpful discussions on this project. We would like to thank Geert Bekaert and seminar participants at Columbia University GSB, Duke Fuqua School of Business, and London Business School for helpful comments. All remaining errors are our own. Please send correspondence to Daniel Paravisini (dp2239@columbia.edu), Veronica Rappoport (ver2102@columbia.edu) and Enrichetta Ravina (er2463@columbia.edu).

1 Introduction

A large body of empirical literature is aimed at estimating parameters that characterize agents' attitudes towards risk and, more generally, the shape of the utility function. Most of the recent results in this area are achieved through laboratory and field experiments based on individual choices across carefully designed lotteries.[1] Validating the experimental results in real life decision making has been hindered, however, by the difficulty of fully characterizing the risk return trade-offs faced by agents. For example, the standard estimation based on portfolio choice between risky and riskless assets cannot fully account for the stochastic characteristics of the risky portion, which includes the return to human capital and other unobservable sources of risk.[2] This has led to the exploration of alternative environments with pure idiosyncratic risk, like race track betting or game shows, to elicit attitudes towards risk in real life decision making.[3]

In this paper, we estimate individual-specific risk preference parameters based on actual financial decisions of investors participating in a peer-to-peer lending platform, Lending Club (LC). This novel environment resembles in a key aspect laboratory experiments: investors are provided with information on the stochatic properties of the investment opportunities so that portfolio choices can be transformed into a selection among well defined lotteries. This allows recovering investors' attitudes towards risk using a marginal indifference condition that parallels the one employed in Holt and Laury (2002) without imposing a specific form for the utility function.

We achieve two goals. First, we test the external validity of experimental findings for a large number of actual investors (2,825) in a relatively small stakes environment (median investment

[1] See for example Holt and Laury (2002), Choi et al. (2007), and Tanaka et al. (2009).

[2] See for example Friend and Blume (1975), Cohn et al. (1975), Morin and Fernandez-Suarez (1983), and Guiso and Paiella (2003).

[3] See for example Jullien and Salanie (2000, 2005), Chiappori et al. (2008, 2009), Bombardini and Trebbi (2007), and Post et al. (2008).

of \$375). Second, we obtain multiple measurements of risk aversion for the same investor over time which we use to compute, separately, the correlation between risk aversion and wealth in the cross section of investors, and the elasticity of risk aversion with respect to changes in wealth for a given investor.

The average relative risk aversion in our sample is 2.85. This value is smaller than estimates obtained from the share of risky assets for Italian households (4.2), and larger than those obtained in laboratory and field experiments, which typically have lower stakes (0.3 to 0.7). [4] The median risk aversion is 1.62, indicating that investor preferences in our sample exhibit a substantial degree of heterogeneity and skewness that are also found in experimental and risky asset share estimates.

Using house prices as an indicator of investor wealth, we find a statistically significant, although economically small, correlation between relative risk aversion and wealth in the cross section. We exploit the substantial decline in house prices during our sample period (October 2007 to April 2008) as a source of variation to estimate the within-person elasticity of risk aversion to a negative wealth shock. We obtain a negative and significant point estimate of −4.2, which indicates that the average investor's relative risk aversion almost doubles to 5.2 when she experiences a 20% decline in house prices in her zip code, the median decline in our sample.

Our estimates are unbiased in the presence of changes over time in investors' risk appraisals, as long as these changes are systematic across all investment opportunities in LC. We test this identifying assumption by comparing the risk aversion exhibited by investors when they make portfolio choices: 1) manually, and 2) through an automatic optimization tool that employs the default probabilities provided by LC to the investors. Estimates obtained from both choices have almost identical distributions, even when obtained from the manual and automatic components

[4] See Guiso and Paiella (2003, 2008), Chiappori et al. (2008), Choi et al. (2007)).

of the same investment choice. The consistency across estimates also holds independently during the first and second halves of our sample period. This implies that the within-investor elasticity estimates are driven by changes investor risk taking behavior.

The results demonstrate that the functional form of investor risk preferences cannot be obtained solely from cross-sectional data. These functional form estimates are confounded with the properties of the joint distribution of risk aversion and wealth. Most empirical evidence on the shape of risk preferences share this common weakness. A notable exception is Chiappori and Paiella (2006), which attempts to disentangle the two phenomena based on financial portfolio invested in risky assets in a panel of Italian households, but finds the bias from the cross sectional estimation to be economically insignificant. In contrast, the bias would lead to severely underestimate the elasticity in our sample: risk aversion and wealth are positively correlated among LC participants, but the individual preference function exhibits decreasing relative risk aversion.

We explore further the relation of risk aversion to other observable investor demographic characteristics. We find that among our pool of investors, women have on average a 15% lower relative risk aversion than men, and investors below 42 years old have a 17% lower risk aversion than those above 42, the median age in our sample. These differences cannot be explained by wealth differences across investors. In contrast, the observed unconditional differences in risk aversion between married and single investors are fully accounted for by wealth differences across the two groups. Overall, the observable characteristics of the investors explain only a small fraction of the heterogenous attitude towards risk in our sample.

We test the consistency of investors' choices within the expected utility framework imposed by our estimation procedure. The expected utility framework delivers testable implications for investment amounts and foregone investments that we take to the data. Regarding investment amounts, if the relative risk aversion decreases (increases) in outside wealth, then we expect the share of wealth invested in LC to increase (decrease) in outside wealth. We corroborate this prediction both in the cross section and within investor estimates. We also show that the risk aversion estimates obtained from portfolio choices, and the revealed preferences implied by the foregone investment opportunities, are consistent. These results validate the rational behavior of investors in the LC platform and confirm our conclusions about the functional form of their risk preferences.

Our estimation strategy is robust to the existence of unobservable outside risky investments, and does not require the computation of the covariance with the market. Following the seminal contribution by Treynor and Black (1973), an investor's portfolio is thought of having three parts: a riskless component, a highly diversified market component, and an active part that consists on securities for which the investor has special insights. We treat the LC portfolio as a part of the latter. Our key assumption is that the returns from LC and those from other assets in the investor's portfolio are correlated only through a common macroeconomic factor. Under this assumption, the holding of market portfolio optimally adjusts to account for the market risk embedded in the LC portfolio. As a result, the portfolio choice in LC depends only the risk aversion of the investor, and the idiosyncratic risk and expected return in LC, for which we have precise estimations.

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. Section 6 shows the results of consistency tests on the portfolio choice model. Section 7 tests some of our identification assumptions, and Section 8 concludes.

2 The Lending Platform

Lending Club (LC) is an online U.S. lending platform that allows individuals to invest in portfolios of small loans. Below, we provide an overview of the platform and derive the expected return and variance of investors' portfolio choices.

2.1 Overview

The platform started operating in June 2007 and until June 2009 generated $59,258,650 worth of loans. 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.[5] LC also posts a default rate for each risk bucket, taken from a long term validation study by TransUnion, based on U.S. unsecured consumer loans. All the loans classified in a given bucket offer the same interest rate, assigned by LC based on an internal rule.

A loan application is posted on the website for a maximum of 14 days. It becomes a loan only if it attracts enough investors and gets fully funded. All the loans have a 3 year term with fixed interest rates and equal monthly installments, and can be prepaid with no penalty for the borrower. At the time the loan is generated a one time fee is assessed on the borrower, ranging

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

from 1.25% to 3.75% depending on the credit bucket. Borrowers more than 15 days late on payment are charged a late fee that is passed to the investors. If he is more than 120 days late, the loan is considered in default, and it enters the collection status. If the collection is successful, the investors receive the amount repaid minus a collection fee that varies depending on the age of the loan and the circumstances of the collection. The information available for each loan is summarized in Table 1.[6]

Prospective investors are encouraged to diversify their investment across loans up to a minimum investment allowed for a given loan of $25.[7] The website provides an optimization tool that suggests the efficient portfolio of loans 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. In our sample, 23.7% of the investors' portfolio choices were made following the optimization tool recommendation.[8]

In order to make sure that the majority of the loans picked by the investors end up getting funded the optimization tool suggests, among all loans in a given credit bucket, those with the highest proportion funded. In addition, LC will directly provide the residual amount necessary to fully fund a loan that has a positive but not full funding status at the time the application expires.

[6] More information on rates and fees can be found at https://www.lendingclub.com/info/rates-and-fees.action.

[7] According to a survey of 1,103 Lending Club investors in March 2009, diversification and high returns relative to alternative investment opportunities are the main motives for investor participation. 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.

[8] Among the remaining 76.3%, some investors used a mixture between the optimization tool recommendation and their own judgement. We exploit this variation in Section 6 to perform identification tests.

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:

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

Since the p_z captures the idiosyncratic probability of default of loans in risk bucket z, the returns are, by construction, independent. The idiosyncratic risk associated with bucket z lowers 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 risk is therefore investor specific:

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

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

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:

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

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 vehicle among the general public. The selection of investors into this program is potentially related with 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 explain why their portfolio departs from just replicating the market.[9]

We also allow for the existence of unobservable outside active risky investments. That is, $z = 1, ..., Z_L$, with $Z_L \leq Z$, correspond to risk buckets in LC. The resulting portfolio of investor i is

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

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:

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

We consider all risk buckets to have the same systematic component. That is, for all $z = 1, ..., Z_L : \beta_z = \beta_L$. This assumption is tested in Section 7.

[9] 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.

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

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

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

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

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

$$x_{Z+1} = x_m + \sum_{z=1}^{Z} x_z \beta_z$$

We use the Sharpe's Diagonal Model for covariance among securities. It posits that the returns of the different investment opportunities are related 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*

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

Then, 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 $z = 1, ..., Z_L$. 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:

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

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 the investor's risk aversion, and the expectation and variance of the independent return of each bucket z.

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. $A^i = \left\{z \leq Z_L | x_z^i > 0\right\}$ –, then for all $z \in A^i$:

$$E\left[R_z\right] = \theta_0^i + ARA^i \cdot W^i x_z^i \cdot var\left[r_z^i\right] \tag{5}$$

The parameter θ_0^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. 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:

$$\theta_0^i \equiv 1 + \beta_L E\left[R_m\right] \tag{6}$$

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

We follow the literature and define the Relative Risk Aversion (RRA) in terms of excess income from the LC investment, that is:

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

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

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 2 compares the demographic characteristics of the LC investors with those of the household heads in the 2007 Survey of Consumer Finances (SCF). The average LC investor is 11 years younger, more likely to be male, less likely to be married, more likely to be a homeowner. 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 net worth, 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. Although geographically disperse, they tend to concentrate in urban areas and major cities. Table 3 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. The full sample contains 2,825 investors, 5,191 portfolio choices, and 50,254 bucket-specific investments. Table 4 (panel 1) reports the descriptive statistics of the bucket-specific investments. The median expected return is 12.2%, with a variance of 3.6%. Table 5 (panel 1) 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 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 upwards. 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 Tables 4 and 5, panel 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 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 (see tables 4 and 5, panel 3). To maintain a consistent analysis sample throughout the discussion that follows, we perform all estimations using this final subsample unless otherwise noted.

5 Results

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:

$$E\left[R_z\right] = \theta_0^i + ARA^i \cdot W^i x_z^i var\left[r_z^i\right] + \varepsilon_z^i \tag{9}$$

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 estimations for four portfolio choices as an example. 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, $W^i x_z^i var\left[r_z^i\right]$. The slope of the linear fit is our estimate of the absolute risk aversion. The number on the top of the plot is the estimated relative risk aversion corresponding to this slope calculated using equation (8).

The error term captures deviations from 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 in Section 7.

The descriptive statistics of the estimated parameters of equation (5) for each portfolio choice and the implied RRA are presented in Table 6. The average RRA across all portfolio choices is 2.85. The distribution is skewed: the median RRA is 1.62 and the standard deviation 3.62.

The median RRA is similar to the estimated in Chiappori and Paiella (2006) based on the share of risky assets in Italian household portfolios, 1.7. Their estimated distribution is also skewed, with an average RRA of 4.2. The laboratory experiments based on lotteries tend to find lower values of RRA, in the range of 0.3 to 0.7 (Holt and Laury, 2002). The observed RRA skewness is also a feature of risk preference distributions obtained in laboratory experiments (Choi, Fisman, Gale, and Kariv, 2007).

The parameter θ_0, defined in equation (6), collects the systematic component of LC. The average estimated θ_0 is 1.09, which indicates that the average investor requires a systematic risk premium of 9%. The estimated θ_0 presents very small variation in the cross section (coefficient of variation 2.8%), when compared to the variation in the risk aversion estimates (coefficient of variation of 67%). This implies relatively common beliefs across investors about the covariance of the returns of investments in LC with the market, β_L.

Table 7 shows how the estimated 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 RRA. This last result is analyzed in more detail in the next subsection.

The risk taking behavior of men and women in our sample has some differences with respect to existing experimental studies. Laboratory experiments that typically employ college students as subjects find that women are more risk averse than men.[10] In our sample, the opposite is true: female investors show lower relative risk aversion. 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.

Interestingly, the same pattern arises in broader environments. Barsky et al. (1997), find that women are more risk averse than men, among participants in the Health and Retirement Study. The sample corresponds to both household heads and spouses between 51 and 61 years old. However, Guiso and Paiella (2008) find that women are slightly less risk averse than men. This result is based on a survey of household heads in Italy. Female heads of the household, who are a disproportionately small fraction, appear to have different risk behavior than the general female population.

Table 8 shows the resulting parameters of estimating a simple OLS regression of RRA on all investor observable characteristics. We find that, except for marital status, the partial correlations between the RRA and investor characteristics have the same sign and significance than the unconditional comparisons. Overall, however, the observable characteristics of the investors explain only a small fraction of the heterogenous attitude towards risk in our sample.

5.1 Risk Aversion and Wealth

This subsection explores the relationship between risk taking behavior and wealth. This exercise highlights that portfolio choices depend not only on the shape of the utility function, but also on the joint distribution of wealth and risk preferences in the population. Disentangling the two effects requires time variation in wealth and multiple measurements of risk aversion for any given individual. We exploit the panel dimension of our data to characterize both the joint

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

distribution of risk aversion and wealth in the population of LC investors, and the elasticity of the individual relative risk aversion with respect to her wealth.

5.1.1 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. Indeed, an important advantage of using house prices is that they vary substantially over time and across zip codes during the sample period. The average house price declines 28.8% between October 2007 and April 2004. In addition, the time series house price variation is heterogeneous across investors: the median house price decline is 20.1%. This will allow us to control for common trends in risk preferences across all investors. Table 9 shows the time series evolution of the distribution of house prices in LC zip codes.

Although house prices are a noisy proxy for wealth, the nature of our question and the features of our empirical analysis limit the importance of such concerns. We use the wealth proxy to compare the risk aversion: 1) across investors of different wealth, and 2) within the same investor after wealth changes. In both cases, our main interest is in the sign of the elasticity of risk aversion to wealth. As long as, on average, wealthier investors live in zip codes with higher median house prices, our wealth proxy will provide us with 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 RRA elasticity to wealth.

In addition, most of 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 controls for all time invariant investor characteristics and thus accounts for these sources of measurement error.

To further explore the features of our wealth shock measure, we calculate the correlation between zip code house price and the imputed investor's net worth as of October 2007, obtained from LC. We find that such correlation is 0.417 for home owners and 0.261 for renters. In what follows, we characterize this relationship for these two groups, and then focus on the subsample of home owners.

5.1.2 Non-Parametric Evidence

Figure 4 shows the relationship between the risk aversion estimates and our wealth shock measure for the cross section of all investors in our sample. The vertical axis plots a kernel-weighted local polynomial smoothing of the risk aversion measure. The horizontal axis measures the (log) median house price at the investor's zip code at the time of the portfolio choice. Absolute risk aversion is decreasing in our wealth proxy, while relative risk aversion is increasing in the wealth proxy.

Figure 5 illustrates this relationship for home owners and renters, separately. As mentioned above, our house price proxy has less measurement error for the investors who are 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 4 should be biased towards zero for the renters. This is confirmed in Figure 5, where the relationship of both ARA and RRA with the wealth proxy is flatter for renters than for home owners. For this reason, all the estimations in the following subsections are performed on the subsample of home owners only.

Finally, we explore the relationship between RRA and wealth by investor gender, age, and marital status in Figure 6. The first noticeable pattern in these plots is that all subgroups exhibit increasing relative risk aversion in the cross section. This implies that the general relationship between risk aversion and our wealth proxy, illustrated in Figure 4, is not driven by any particular subgroup. Also, female investors in our sample exhibit a larger propensity to take risk at all wealth levels. The same can be said for younger investors, although the difference is not statistically significant at higher wealth levels. In contrast, married and single investors exhibit the same level of RRA across all wealth levels. However, as married investors are typically wealthier, their unconditional risk aversion is larger than for single investors.

5.1.3 Parametric Evidence: Cross Sectional and Within Investor

We estimate the cross sectional elasticity of risk aversion to wealth using the following pooled OLS regression:

$$\ln\left(RiskAversion_{it}\right) = \beta_0 + \beta_1 \ln\left(HouseValue_{it}\right) + \delta_t + \omega_{it}. \tag{10}$$

The left hand side variable is the (log) measure of risk aversion obtained for investor i for a portfolio choice at month t. Because different investors can make investment choices at different times, we include quarter dummies in some of the specifications, to account for systematic differences across quarters due to macroeconomic factors.

Table 10 shows the estimated cross sectional elasticity β_1 for ARA (columns 1 and 2) and RRA (columns 3 and 4). All the estimates are statistically significant at the 1% confidence level and confirm the non-parametric relationships from the previous subsection: wealthier investors exhibit lower absolute risk aversion and larger relative risk aversion. The magnitude of the cross sectional elasticity of the RRA to our wealth proxy does not appear to be economically significant. The conservative estimate for the RRA of $\beta_1 = 0.18$ 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 a RRA of 3 instead of the overall mean of 2.85.

These estimates are comparable with Guiso and Paiella (2008). However, we cannot interpret the elasticity based on cross section variation as a description of the form of the utility function. Such interpretation is only valid when the joint distributions of wealth and risk aversion in the population are independent.[11] 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 (10) augmented with investor specific dummies as controls (investor fixed effects):

$$\ln\left(RiskAversion_{it}\right) = \alpha_i + \beta_2 \ln\left(HouseValue_{it}\right) + \delta_t + \omega_{it}. \tag{11}$$

The elasticity β_2 is estimated from the sensitivity of risk aversion to changes in the wealth proxy for the same investor. The estimate is obtained only for those investors that choose an LC portfolio more than once in our sample period. The average number of portfolio choices by investor in the sample is 1.8, and the cross sectional results above are unchanged when estimated on the subsample of investors that chose portfolios more than once. Cross sectional differences in risk aversion levels are fully accounted for by the investor fixed effects, while the quarter dummies account for aggregate trends in risk aversion over time across all investors.

The estimated wealth elasticities of ARA and RRA are shown in Table 11. The sign of the estimated within-investor elasticity of ARA to wealth is the same as in the cross section: absolute risk aversion is decreasing in investor wealth. In contrast, the estimated sensitivity of an investors RRA to a wealth change is negative and both statistically and economically significant. The conservative point estimate of $\beta_2 = -4.2$ indicates that the average investor's RRA increases from 2.85 to 4.0 when she experiences a 10% decline in house prices in her zip

[11] Chiappori and Paiella (2006) 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.

code.

These results indicate that although wealthier investors are slightly more risk averse, investors exhibit substantial decreasing relative risk aversion. These findings highlight the importance of estimating the elasticity of risk aversion to wealth using panel data to avoid the confounding effects of the unobserved joint distribution of wealth and risk preferences in the population.

6 Consistency Tests

In this section we test the consistency of the investors' choices. First, we compare the risk and return of the risk buckets in the investor's portfolio to those she did not choose (*foregone* buckets). We confirm that the investor's choice is optimal: including the foregone risk buckets in the investor's portfolio would lower her utility, given her estimated preferences. Second, we test an additional prediction of the model in section 3. Instead of focusing on the marginal arbitrage condition between active buckets, we analyze how the total amount invested in LC changes across investors with different wealth and, for a given investor, following a wealth shock. Our findings are consistent with the risk aversion elasticities computed in section 5. Overall, these tests suggest that the investors make sophisticated portfolio decisions, consistent with the expected utility framework.

6.1 Foregone Risk Buckets

The median investor in our sample assigns funds to 10 out of 35 risk buckets (see Table 5, panel 3). 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 within the expected utility framework.

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:

$$foc_{foregone} = E\left[R_z\right] - \theta_0^i + ARA^i\left(25\right) var\left(r_z\right) < 0$$

We test this prediction by calculating $foc_{foregone}$ for every foregone bucket using the parameters $\left\{\theta_0 = \hat{\theta}_0^i, RRA^i = \widehat{RRA}^i\right\}$ 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 $\hat{\theta}_0^i$ and an absolute risk aversion $\widehat{RRA}^i$ using specification (9). For each of the 25 foregone risk buckets we calculate $foc_{foregone}$ above. Then we repeat the procedure for each of the investments 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.

6.2 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, that when relative risk aversion decreases (increases) in outside wealth, then the share of wealth invested in LC will increase (decrease) in outside wealth. We can use these predictions to provide an independent validation for the results on the elasticity of risk aversion to wealth, which are based on risk aversion estimates obtained from the arbitrage condition between active risk buckets in equation (5).

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

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

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 $\widetilde{x}_z \equiv x_z / \sum_{z=1}^{Z_L} x_z$. A linearization of the first order condition around expected consumption results in the following optimality condition:

$$E\left[R_L\right] - 1 = ARA^i \cdot W^i x_m^i \cdot cov\left[R_m, R_L\right] + ARA^i \cdot W^i x_L^i \cdot var\left[r_L\right] \tag{12}$$

The total amount invested in LC is typically very small relative to our proxy of investors' wealth. According to Table 5, the median investment in LC represents 0.11% of our proxy for the investor's house value. Then, the optimal composition of the outside portfolio can be approximated by the following expression[12]:

$$E\left[R_m\right] - 1 = ARA^i \cdot x_m^i W^i \cdot var\left[R_m\right]$$

It follows that $ARA^i x_m^i W^i = \sigma$ is constant across investors and, therefore, $ARA^i W^i x_m^i cov\left[R_m, R_L\right] =$

[12] In terms of section 3, this is equivalent to $Z = Z_L$ and $\sum_{z=1}^{Z_L} x_z \beta_z \to 0$.

θ is also constant. Then, equation (12) can be restated as:

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

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

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

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

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 relative risk aversion, 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 (10) and (11) using the (log) amount invested in LC and the ratio of investment in LC to our proxy for housing wealth. The estimated cross sectional and within investor elasticities are shown in Table 12. The investment amount is increasing with investor house values in the cross section, while the ratio of the investment to house value is decreasing. These estimates are consistent with the decreasing ARA and increasing RRA cross sectional elasticities found in the previous section and reported in Table 10.

The within investor estimates indicate that the total funds in LC also increases with investor's wealth. However, the sign of the elasticity of the ratio of investment to housing wealth switches relative to the cross sectional one. The ratio of investment to our wealth proxy increases with wealth, which is consistent with the decreasing relative risk aversion parameter shown in Table 12.

This results indicate that our conclusions regarding the distribution of risk preferences in the population as well as the individual risk preferences obtained from the investor fixed effect estimation are robust across different model implications.

7 Identification Tests

This section explores the validity of our identification assumptions. First, it checks that the optimization tool provided by the website does not bias our results. Second, it tests whether investors disagree with the LC assumption that all loans have the same systematic risk and consider buckets to have different covariance with the market. Finally, it test that assumption 1, which implies that loans are not used to hedge other sources of risk in a way that varies systematically across risky buckets, holds in the data.

7.1 The optimization tool

Our model in section 3 is based on the assumption that investors choose their own optimal portfolio. However, many portfolio decisions on the platform are made with the help of the optimization tool, available in the LC website.

The portfolio suggested by the tool is never superior to the one implied by condition (5). This is because the optimal shares in each LC bucket derived in section 3 minimize the variance of the entire risky portfolio given a required expected return; while the shares suggested by the tool minimize the variance of the LC portfolio only. It is shown in the Appendix that the condition that characterizes the *Automatic* choices, parallel to equation (5) in section 3, is:

$$E\left[R_z\right] = \theta^i_{0,A} + \left(ARA^i \cdot \frac{E\left[R_L\right] - \theta^i_{0,A}}{E\left[R_L\right] - \theta^i_{0,N}}\right) \cdot W^i x^i_z \cdot var\left[r_z\right]$$

where $\theta^i_{0,N}$ and $\theta^i_{0,A}$ correspond to the investor specific constant when the investment is *Non Automatic* and *Automatic*, respectively:

$$\begin{aligned}
\theta^i_{0,A} &= \lambda^i_1 + \beta_L E\left[R_m\right] \\
\theta^i_{0,N} &= 1 + \beta_L E\left[R_m\right]
\end{aligned}$$

λ^i_1 is a constant, derived in the Appendix.

Then, our estimates from the specification (9) may be biased by the inclusion of the *Automatic* investments:

$$bias^i = \frac{E\left[R_L\right] - \theta^i_{0,A}}{E\left[R_L\right] - \theta^i_{0,N}} - 1.$$

To measure the potential bias, we focus on portfolio choices that have both *Non Automatic* and *Automatic* investments. For the same investor, we estimate $\theta^i_{0,N}$ as the constant parameter in equation (9), using only *Non Automatic* investments. Correspondingly, we estimate $\theta^i_{0,A}$ based on the same specification, but using only those buckets allocations suggested by the optimization tool. Figure 7 depicts an example of this comparison. Panel A shows the expected return and weighted variance of all *Automatic* investments in a portfolio, while panel B includes only the *Non Automatic* buckets. In this example, the estimated constants are 1.07 in both cases, indicating no significant bias.

We perform the same calculations for the subsample of investors that have at least two *Automatic* and two *Non Automatic* investments and report the estimated parameters in Table

13. The moments of the distribution of θ_0 are virtually identical across the two estimations. Moreover, θ_0 is also constant in the cross section of investors. The median parameter is 1.08 for investors whose entire portfolio is based on the suggestion of the optimization tool and for investors that choose all loans manually. We are therefore confident that the inclusion of *Automatic* investments does not bias our estimation of risk aversion.

7.2 Differences in Systematic Component across Buckets

The optimal LC portfolio, characterized by equation (5), depends on the stochastic properties of the independent return, r_z; that is, the non systematic component of the bucket return, R_z :

$$R_z = \beta_z \cdot R_m + r_z.$$

Section 3 follows the LC assumption and considers all risk buckets to have the same sensitivity to the systematic component: for all $z = 1, ..., Z_L : \beta_z = \beta_L$.

However, investors may not agree with the LC assumption and consider buckets to have different covariance with the market. In such case the equation characterizing the investor's optimal portfolio is given by:

$$E[R_z] = \theta_0^i + \left(ARA^i + (\beta_z - \beta_L) \frac{E[R_m]}{W^i x_z^i \cdot var[r_z]} \right) \cdot W^i x_z^i \cdot var[r_z]$$

where $\theta_0^i = 1 + \beta_L E[R_m]$, recovers the average sensitivity of the investor's LC portfolio, β_L. This may introduce a bias in the risk aversion parameter estimated with equation (9).

To measure the potential bias, we focus again on portfolio choices that have both *Non Automatic* and *Automatic* investments. The optimization tool constructs the optimal portfolio under the assumption that all buckets have the same systematic component, i.e. $\beta_z = \beta_L$.[13] And we concluded in the previous subsection that the risk aversion parameter estimated from *Automatic* investments is unbiased. Then, we test whether investors' assumption about the stochastic properties of the buckets differ from LC guidelines by comparing the estimates based on *Automatic* investments with those based on *Non Automatic* choices. Figure 7 depicts an example of this comparison.[14]

Table 13, panel 1, reports the estimated ARA for the subsample of investors that have at least two *Automatic* and two *Non Automatic* investments. The moments of the distribution of ARA are virtually identical across the two estimations for any given investor. In addition, panels 2 and 3 of Table 13 show that this holds true both in the first and second half of the sample period. We also confirm that the median ARA is 0.0440 for investors whose entire portfolio is suggested by the tool, and it is 0.0441 for investors who choose manually, indicating that there are no systematic differences in the ARA estimates across the two types of investors.

These results suggest that investors' beliefs about the stochastic properties of the loans in LC do not differ substantially from the ones posted on the website, i.e. $\beta_z = \beta_L$ for all z. The resulting estimates based on that benchmark are therefore unbiased. In addition, these result imply that investors beliefs about the accuracy of the LC default probabilities does not vary systematically over time and thus cannot explain the observed increase in investor risk aversion obtained in Section 5.1.

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

[14] Panel A shows the expected return and weighted variance of all *Automatic* investments in a portfolio, while panel B includes only the *Non Automatic* buckets. In this example, the estimated absolute risk aversion are 0.048 and 0.051 respectively.

7.3 Distance

A potential failure of our identification assumptions may arise from the violation of the Sharpe's Diagonal Model, which assumes that loans are related to the investor's outside wealth only through a common systematic component. 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 proxy for hedging motives in our context is geographical location, with investors potentially picking loans in distant areas to hedge their income risk. In Table 14, we show that there is no systematic variation across buckets in the geographical distance between borrowers and investors. These findings validate the identification assumption that hedging motives, if present, do not vary systematically across budgets.

8 Conclusion

In this paper we estimate risk preference parameters and their elasticity to wealth based on the actual financial decisions of a panel of U.S. investors participating in person-to-person lending. We find a large degree of heterogeneity in the relative risk aversion parameter, with an average RRA of 2.85 and a median of 1.62.

Using house prices as a proxy for investor wealth, we also find a statistically significant, although economically small, correlation between relative risk aversion and wealth in the cross section and a both economically and statistically significant negative relation within each investor. Our most conservative estimate of the elasticity of risk aversion to wealth of -4.2 indicates that the average investor's relative risk aversion almost doubles to 5.2 when she experiences a

20% decline in house prices in her zip code, the median decline in our sample period (October 2007 to April 2008).

Finally, we test investors' consistency and rationality by investigating the relationship between the share of wealth invested in LC and outside wealth, and by analyzing the information about investors' risk preferences contained in investment vehicles that were available to them at the time of their choices and that they decided not to take. We find that the risk aversion estimates obtained from portfolio choices, and the revealed preferences from the foregone investments, are consistent. These tests validate the rational behavior of investors in the LC platform and confirm our conclusions about the functional form of their risk preferences.

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9 Appendix: 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 (5):

$$E\left[r_L\right] - 1 = ARA^i \cdot W^i x_L^i \cdot var\left[r_L\right] \tag{13}$$

$\left(E\left[r_L\right] - 1\right)/var\left[r_L\right]$ 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 I 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, 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 $s_z > 0$:

$$s_z = \lambda_0^i \frac{E\left[r_z\right] - \lambda_1^i}{var\left[r_z\right]} \tag{14}$$

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:

$$\lambda_0^i = \frac{var\left[r_L\right]}{E\left[r_L\right] - \lambda_1^i} \tag{15}$$

From the Automatic portfolio composition is therefore possible to recover the investor's preferred risk-return ratio. Combining equations (14) and (15) with the optimal LC investment condition (13), we obtain the following expression:

$$E\left[R_z\right] = \left(\beta_L E\left[R_m\right] + \lambda_1^i\right) + ARA^i \cdot W^i x_L^i s_z^i \cdot var\left[r_z\right] \frac{\left(E\left[r_L\right] - \lambda_1^i\right)}{\left(E\left[r_L\right] - 1\right)} \tag{16}$$

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* investments. The magnitude of the bias is:

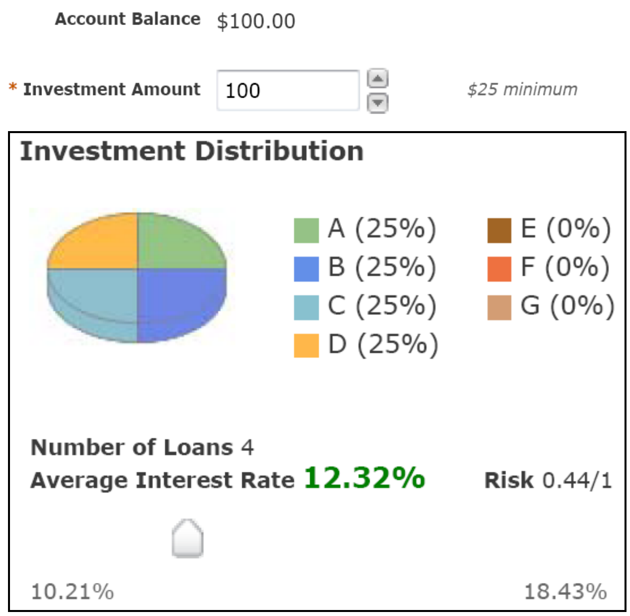
$$bias^i = \frac{E\left[R_L\right] - \theta_{0,A}^i}{E\left[R_L\right] - \theta_{0,N}^i} - 1.$$

where $\theta_{0,N}^i$ and $\theta_{0,A}^i$ correspond to the investor specific constant in the specification equations (5) and (16) respectively:

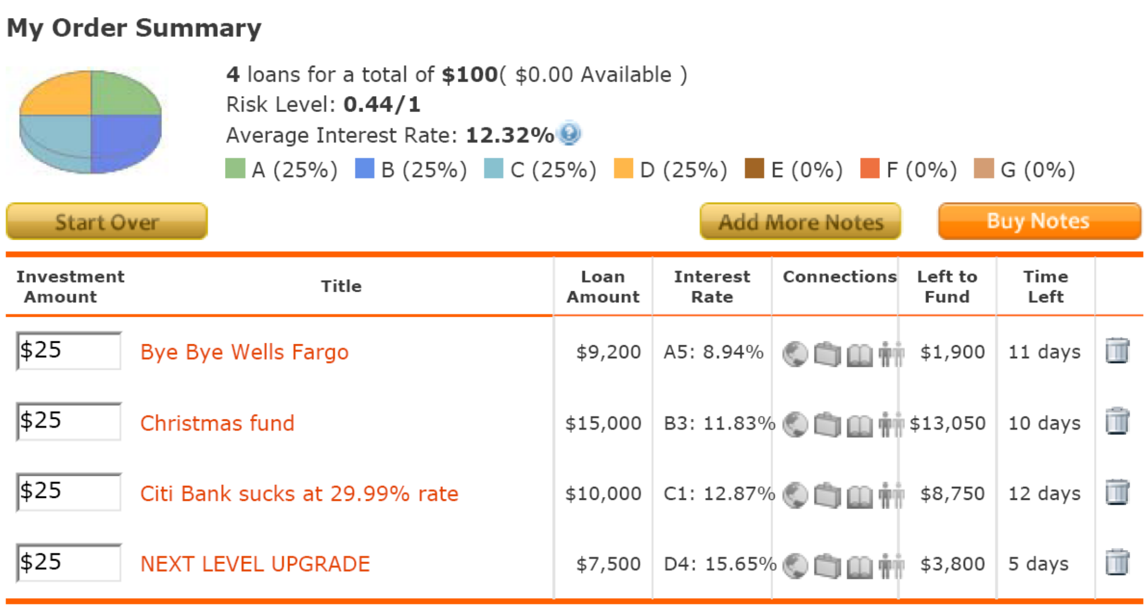
$$\begin{aligned} \theta_{0,A}^i &= \lambda_1^i + \beta_L E\left[R_m\right] \\ \theta_{0,N}^i &= 1 + \beta_L E\left[R_m\right] \end{aligned}$$

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

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



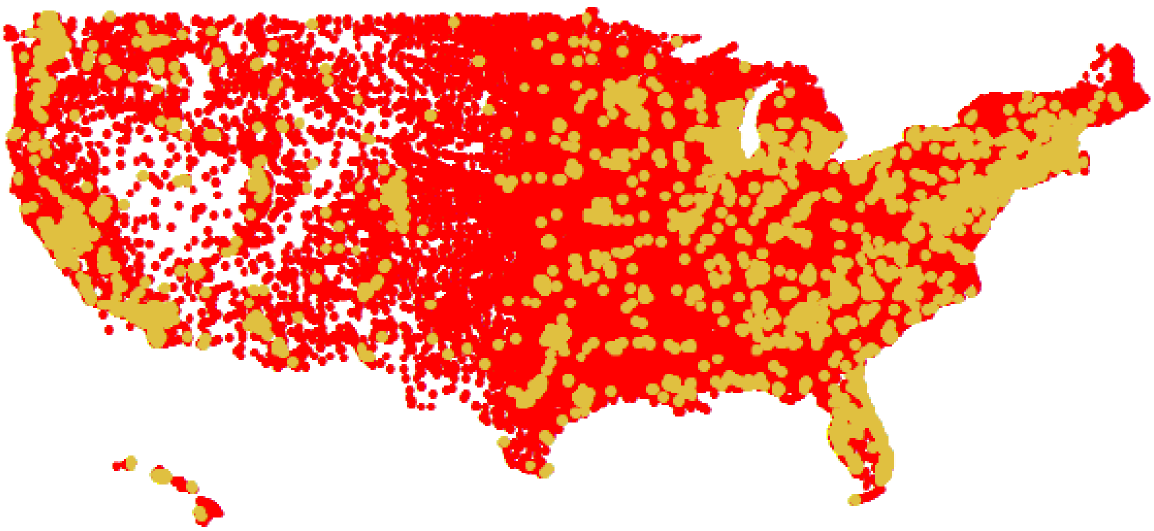
B. Screen 2: Suggested Portfolio Summary



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

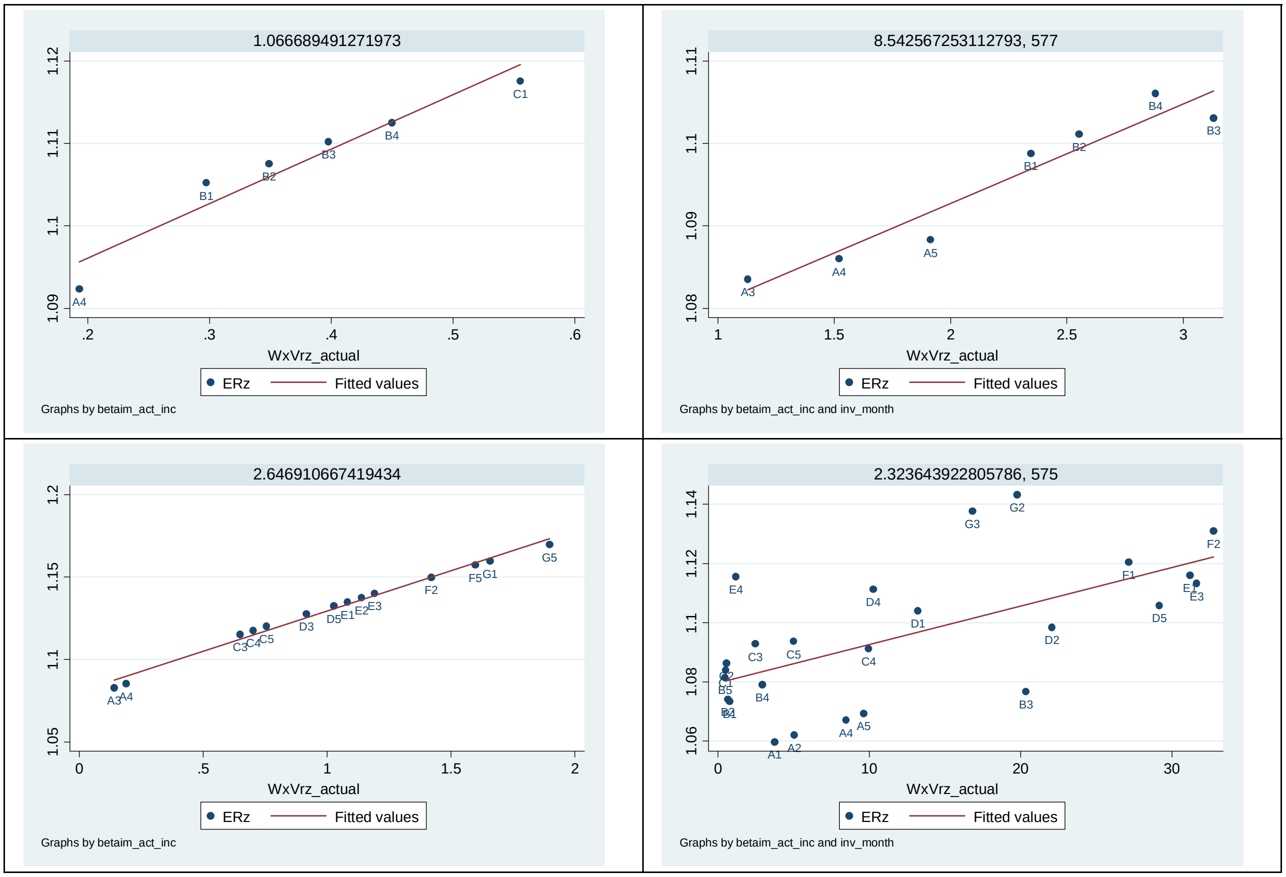
The website provides an optimization tool that suggests the efficient portfolio of loans for the investor's preferred risk return trade-off, under the assumption that loans are uncorrelated with each other and any outside investment opportunity. Once a portfolio has been formed, the investor is shown the loan composition of her portfolio on a new screen, she can look at each loan individually, change the amounts allocated to some of the loans, drop them altogether, or add others.

Figure 2: Geographical Distribution of Lending Club Investors



The dots represent zip code centroid locations. In yellow: zip codes with Lending Club investors. In red: other zip codes.

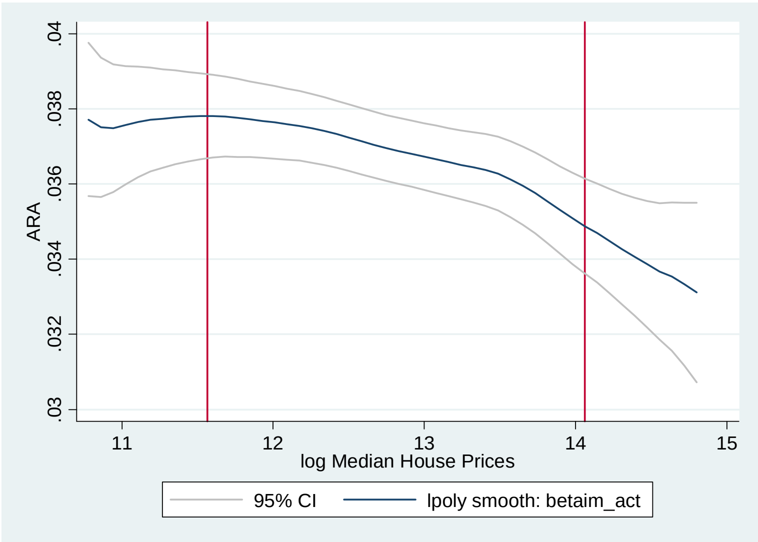
Figure 3: Examples of Risk Return Choices and Estimated RRA



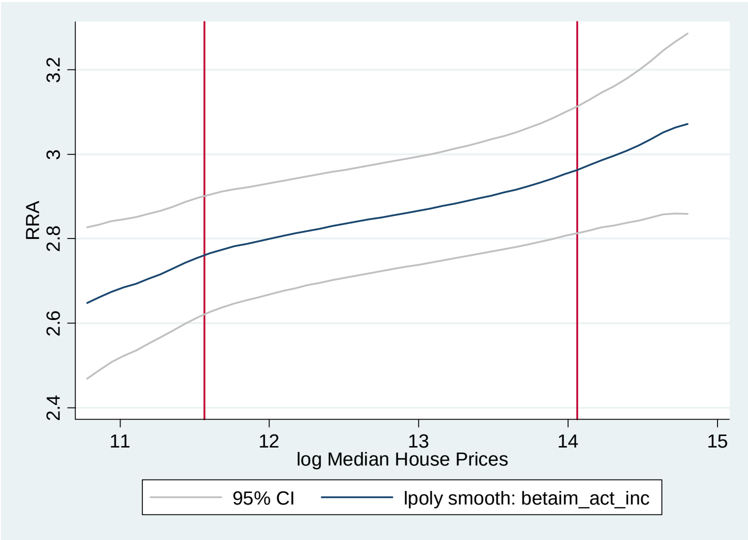
Each plot represents one investment in our sample. The dots represent the risk and weighted return of each of the buckets that compose the portfolio choice. The dots are labeled with the corresponding risk classification of the bucket. The vertical axis measures the expected return of a risk bucket, 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. The number on the top of the plot is the estimated relative risk aversion that corresponds to this slope.

Figure 4: Risk Aversion and Wealth in the Cross Section

A. Absolute Risk Aversion



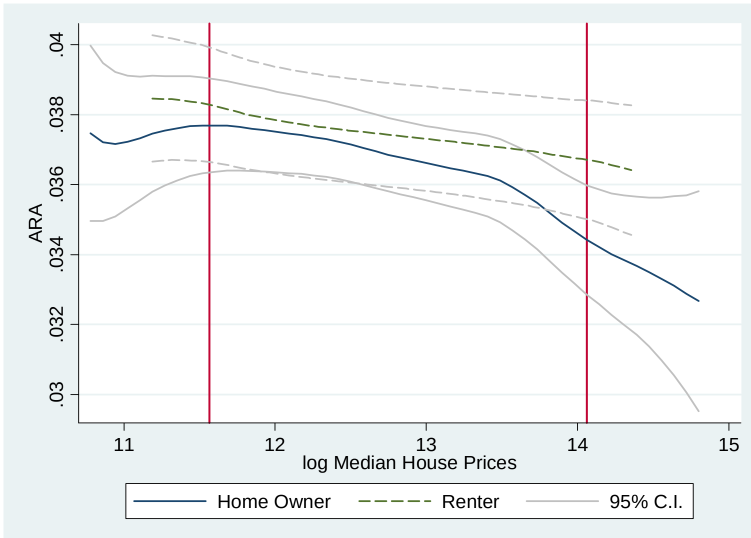
B. Relative Risk Aversion



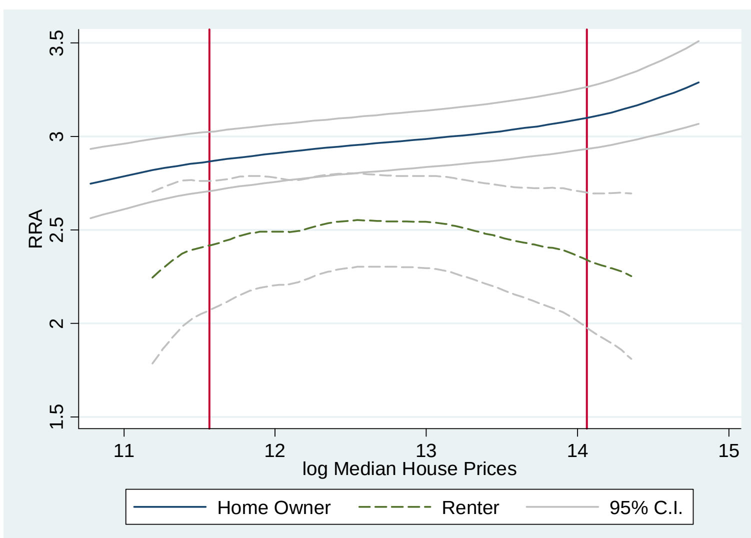
The vertical axis plots a weighted local polynomial (degree zero) smoothing of the risk aversion measure. The observations are weighted using an Epanechnikov kernel with a bandwidth of 0.75. The horizontal axis measures the (log) median house prices at the investor's zip code at the time of the portfolio choice, our proxy for investor wealth.

Figure 5: Risk Aversion and Wealth in the Cross Section: Home Owner Renter Comparison

A. Absolute Risk Aversion



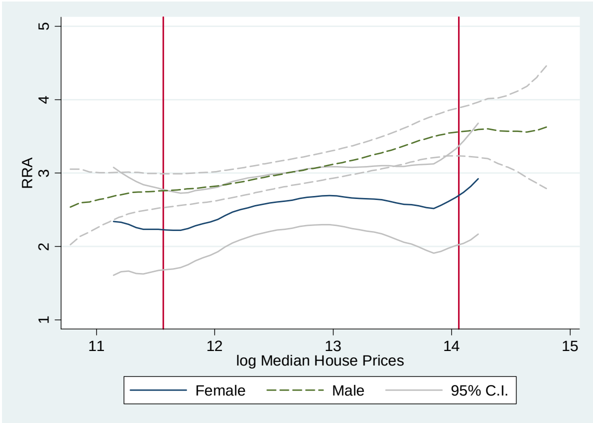
B. Relative Risk Aversion



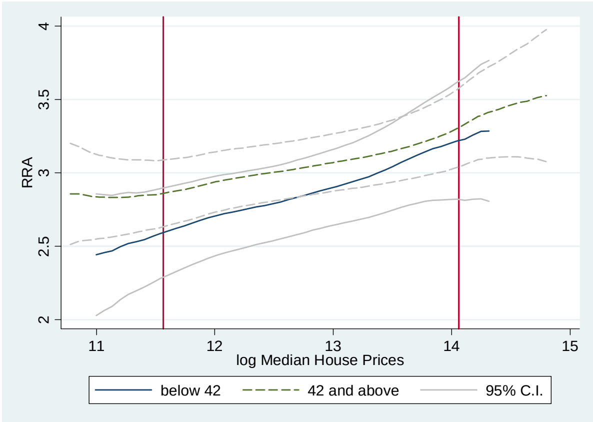
The vertical axis plots a weighted local polynomial (degree zero) smoothing of the risk aversion measure. The observations are weighted using an Epanechnikov kernel with a bandwidth of 0.75. The horizontal axis measures the (log) median house prices at the investor's zip code at the time of the portfolio choice, our proxy for investor wealth.

Figure 6: Relative Risk Aversion and Wealth in the Cross Section: Investor Characterstics

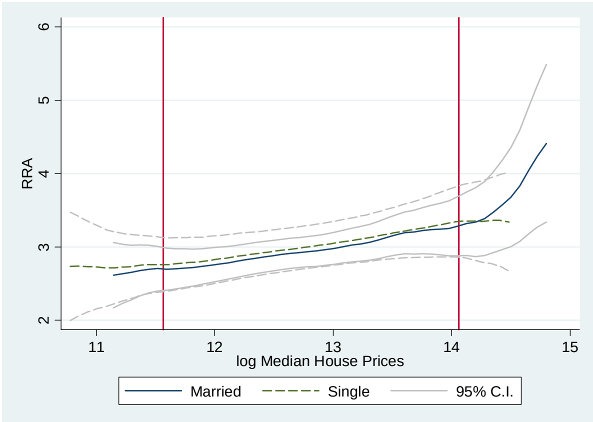
A. By Gender



B. By Age



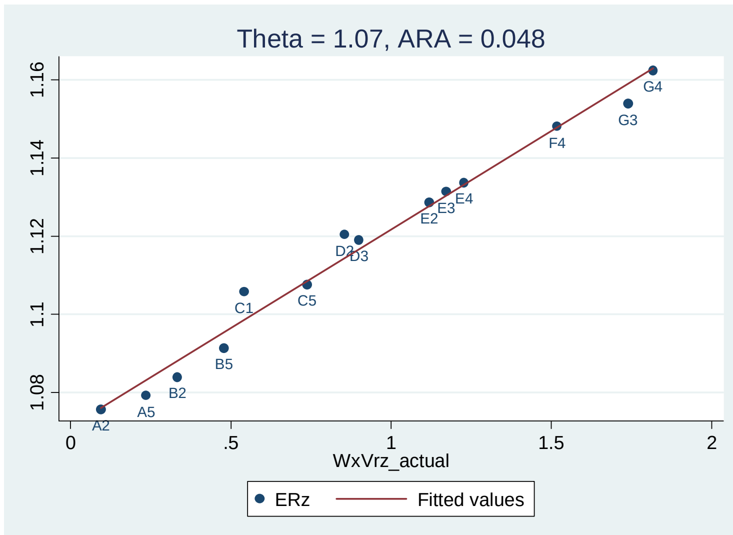
C. By Marital Status



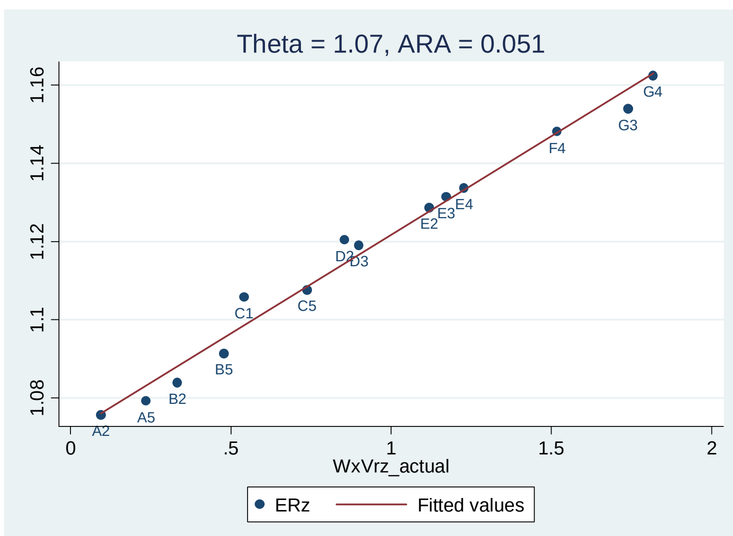
The vertical axis plots a weighted local polynomial (degree zero) smoothing of the risk aversion measure. The observations are weighted using an Epanechnikov kernel with a bandwidth of 0.75. The horizontal axis measures the (log) median house prices at the investor's zip code at the time of the portfolio choice, our proxy for investor wealth.

Figure 7: Example of Estimated Risk Aversion Excluding Investor Deviations from the Portfolio Tool Suggestions

A. Using Automatic Buckets



B. Using Non-Automatic Buckets



Both plots represent the same actual investment example. The dots on the top plot represent the risk and weighted return of the buckets that compose the portfolio choice that were chosen by the portfolio tool (automatic). The bottom plot includes buckets directly chosen by the investor (Non-Automatic). The number on the top of each plot is the implied relative risk aversion in each case.

Table 1: Borrower Characterstics

Source: Lending Club. Sample period: October 2007 to April 2008. FICO scores, 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. pN represents the N^{th} percentile of the distribution.

Variable	mean	sd	p1	p25	p50	p75	p99	N
FICO score	694.3	38.2	640.0	664.0	688.0	717.0	797.0	1,661
Debt to Income	0.128	0.076	0.000	0.066	0.128	0.188	0.288	1,661
Monthly Income ($)	5,427.6	5,963.1	800.0	3,000.0	4,250.0	6,416.7	20,833.3	1,661
Amount borrowed ($)	9,223.7	6,038.0	600.0	5,000.0	8,000.0	12,000.0	25,000.0	1,661

Table 2: Investor Characteristics

Sources: Lending Club and Survey of Consumer Finances 2007. Sample period for Lending Club investors: October 2007 to April 2008. Lending Club recovers investor characteristics through a third party marketing firm (Axciom). Axciom uses a proprietary algorithm to recover gender from the investor names, and matches investor names, home addresses, and credit history details to available public records to recover age, marital status, and home ownership status.

	Lending Club Investors			SCF Household Heads		
Variable	**Mean**	**Median**	**Std**	**Mean**	**Median**	**Std**
Male	83%	100%		79%	100%	
Age	43	40	15	52	51	16
Married	56%	100%		68%	100%	
Home Owner	75%	100%		69%	100%	

Table 3: Zip Code Median House Prices, by LC investor location

Sources: Lending Club and Zillow. We use investor zip codes to match the LC data with real estate price data. 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. pN represents the N^{th} percentile of the distribution.

Median Zip Code House Values (x $1000)	**mean**	**sd**	**p1**	**p25**	**p50**	**p75**	**p99**	**N**
LendingClub Investor zip codes	374.9	266.2	82.6	194.8	301.4	480.8	1,434.4	1,624
Other zip codes	254.9	202.6	55.4	130.8	200.6	315.4	995.4	9,017

Table 4: Descriptive statistics, investor-bucket-month

Each observation represents an investment allocation by investor i in bucket z at month t. Investment is the amount allocated to the bucket in dollars. # projects counts the number of loans inside the risk bucket that conform the investment. Loans are assigned to risk buckets according to the amount of the loan, the FICO score, and other borrower characteristics. Interest and default rates are the same for all projects in a bucket. The expectation and variance of the investment return in a bucket are calculated assuming a geometric distribution for the idiosyncratic monthly survival probability of the individual loans and independence across loans in the same bucket. The analysis sample excludes portfolio choices in a single bucket and non-diversified investments. The analysis subsample excludes portfolio choices made by investors located in zip codes that are not covered by the Zillow Index. pN represents the N^{th} percentile of the distribution.

Variable	mean	sd	p1	p25	p50	p75	p99	N
1. All Investments								
Investment ($)	302.8	2,251.4	25.0	25.0	50.0	100.0	5,200.0	50,254
# Projects in Bucket	1.9	1.8	1.0	1.0	1.0	2.0	9.0	50,254
Interest Rate	12.89%	2.98%	7.43%	10.46%	12.92%	15.13%	18.61%	50,254
Default Rate	2.77%	1.45%	0.32%	1.58%	2.69%	3.95%	5.53%	50,254
E(PV $1 investment)	1.122	0.027	1.062	1.104	1.122	1.142	1.177	50,254
Var(PV $1 investment)	0.036	0.020	0.004	0.020	0.035	0.051	0.077	50,254
2. Analysis sample: Investments in at least 2 buckets, diversified investments								
Investment ($)	86.0	206.9	25.0	25.0	50.0	75.0	750.0	43,662
# Projects in Bucket	2.0	1.8	1.0	1.0	1.0	2.0	9.0	43,662
Interest Rate	12.91%	2.96%	7.43%	10.59%	12.92%	15.13%	18.61%	43,662
Default Rate	2.78%	1.45%	0.32%	1.58%	2.84%	3.95%	5.53%	43,662
E(PV $1 investment)	1.122	0.027	1.062	1.104	1.123	1.142	1.177	43,662
Var(PV $1 investment)	0.027	0.020	0.002	0.010	0.022	0.039	0.076	43,662
3. Analysis subsample: with real estate data								
Investment ($)	90.1	220.5	25.0	25.0	50.0	75.0	825.0	37,248
# Projects in Bucket	2.0	1.8	1.0	1.0	1.0	2.0	9.0	37,248
Interest Rate	12.92%	2.97%	7.43%	10.59%	12.92%	15.13%	18.61%	37,248
Default Rate	2.79%	1.45%	0.32%	1.58%	2.84%	3.95%	5.53%	37,248
E(PV $1 investment)	1.122	0.027	1.062	1.104	1.123	1.142	1.177	37,248
Var(PV $1 investment)	0.036	0.020	0.004	0.020	0.035	0.051	0.077	37,248

Table 5: Descriptive statistics, investor-month

Each observation represents a portfolio choice by investor i at month t. Investment is the total amount allocated to the new Lending Club portfolio. # buckets (projects) counts the number of buckets with a positive investment (loans that conform the portfolio). The expectation and variance of the investment return in a bucket are calculated assuming a geometric distribution for the idiosyncratic monthly survival probability of the individual loans and independence across loans in the same bucket. Median house price of the zip code where the investor is located comes from the Zillow Home Value Index. Investment/House Value is calculated using the median house price as a proxy for house value. The analysis sample excludes portfolio choices in a single bucket and non-diversified investments. The analysis subsample excludes portfolio choices made by investors located in zip codes that are not covered by the Zillow Index. pN represents the N[th] percentile of the distribution.

Variable	mean	sd	p1	p25	p50	p75	p99	N
1. All Investments								
Investment	2,931.6	28,402.4	25.0	100.0	375.0	1,000.0	35,975.0	5,191
# Buckets	9.7	8.7	1.0	2.0	7.0	15.0	32.0	5,191
# Projects	18.8	28.0	1.0	2.0	8.0	22.0	138.0	5,191
E(PV $1 investment)	1.121	0.023	1.068	1.105	1.121	1.136	1.172	5,191
Var(PV $1 investment)	0.0122	0.0159	0.0012	0.0026	0.0054	0.0143	0.0746	5,191
Median House Price in Zip Code	407,566	300,482	81,657	201,872	307,106	524,176	1,596,490	4,321
% Investment/House Value	0.466%	2.462%	0.003%	0.030%	0.110%	0.339%	5.598%	4,321
2. Analysis sample: Investments in at least 2 buckets, diversified investments								
Investment	1,002.7	2,736.2	50.0	125.0	375.0	850.0	9,975.0	3,745
# Buckets	11.7	8.4	2.0	4.0	10.0	17.0	32.0	3,745
# Projects	23.3	28.9	2.0	5.0	14.0	30.0	145.0	3,745
E(PV $1 investment)	1.121	0.021	1.071	1.106	1.121	1.135	1.167	3,745
Var(PV $1 investment)	0.0052	0.0065	0.0002	0.0012	0.0025	0.0063	0.0309	3,745
Median House Price in Zip Code	413,626	296,276	81,475	205,798	315,214	531,963	1,521,711	3,145
% Investment/House Value	0.336%	0.861%	0.007%	0.042%	0.115%	0.305%	3.502%	3,145
3. Analysis subsample: with real estate data								
Investment	1,067.0	2,934.3	50.0	125.0	400.0	900.0	10,425.0	3,145
# Buckets	11.8	8.5	2.0	4.0	10.0	18.0	32.0	3,145
# Projects	23.8	29.5	2.0	5.0	14.0	30.0	145.0	3,145
E(PV $1 investment)	1.121	0.021	1.071	1.106	1.121	1.135	1.167	3,145
Var(PV $1 investment)	0.0066	0.0070	0.0012	0.0023	0.0038	0.0079	0.0342	3,145
Median House Price in Zip Code	413,626	296,276	81,475	205,798	315,214	531,963	1,521,711	3,145
% Investment/House Value	0.336%	0.861%	0.007%	0.042%	0.115%	0.305%	3.502%	3,145

Table 6: Unconditional distribution of estimated parameters and implied RRA

Absolute Risk Aversion (ARA) and constant θ_0 obtained through the OLS estimation of the following relationship for each investment:

$$E(r_z) = \theta_0^i + ARA^i I^i x_z^i Var^i(r_z) + \varepsilon_z^i$$

where the left (right) hand side variable is expected return (idiosyncratic variance times the investment amount) of the investment in bucket z. The 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.

Variable	ARA	θ_0	Expected Income	RRA
Mean	0.03679	1.09	130.15	2.85
sd	0.02460	0.03	344.25	3.62
p1	-0.00837	1.05	4.11	-0.16
p5	0.00407	1.05	5.89	0.20
p25	0.02271	1.08	16.03	0.56
p50	0.04395	1.09	45.91	1.62
p75	0.04812	1.09	111.11	3.66
p95	0.06179	1.12	475.81	10.25
p99	0.08562	1.16	1,255.14	17.18
N	3,145	3,145	3,145	3,145

Table 7: RRA by Observable Investor Characteristics

Relative Risk Aversion (RRA) obtained as in Table 6. 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.

	Gender			**Age**			**Marital Status**			**Home Ownership**			**Zip Code House Values**		
	Female	**Male**	**Δ**	**< 42**	**42 and above**	**Δ**	**Single**	**Married**	**Δ**	**Renter**	**Home Owner**	**Δ**	**< median**	**> median**	**Δ**
Mean	2.54	2.92	**0.38 ****	2.62	3.05	**0.44 *****	2.74	2.93	**0.19 ***	2.44	2.97	**0.53 *****	2.68	3.03	**0.35 *****
sd	3.14	3.71		3.47	3.74		3.47	3.73		3.12	3.76		3.50	3.75	
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	

Table 8: Pooled OLS Regression of RRA on Investor Characteristics

Estimated parameters of the pooled OLS regression of Relative Risk Aversion (RRA) on indicators of investor gender, age above median (log age in column 2), marital status, home ownership status, house price in zip code above the median (log median house price in column 2). Standard errors clustered at the investor level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Dependent Variable:	RRA	
	(1)	(2)
Female = 1	-0.401**	-0.410**
	(0.1810)	(0.1810)
Age above median (42) = 1	0.304*	
	(0.1620)	
ln(age)		0.490**
		(0.2450)
Married = 1	-0.0300	-0.0340
	(0.1610)	(0.1600)
Home Owner = 1	0.480***	0.433**
	(0.1820)	(0.1930)
House Value above median = 1	0.400***	
	(0.1470)	
ln(House Value)		0.325***
		(0.1150)
R-squared (adj)	0.008	0.009
Observations	3,145	3,141

Table 9: Time Series of House Prices in Sample Period

Descriptive statistics of the median zip code house price where Lending Club investors are located by month. pN represents the N^{th} percentile of the distribution. The bottom row shows the percentage decline of the statistic between October 2007 and April 2004.

Month	mean	sd	p1	p25	p50	p75	p99
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%

Table 10: Risk Aversion and Wealth in the Cross Section

Elasticity of risk aversion to wealth in the cross section, obtained through the following pooled OLS estimation:

$$\ln(RiskAversion_{it}) = \beta_0 + \beta_1 \ln(HouseValue_{it}) + \delta_t + \omega_{it}$$

where the left hand side variable is the (log) measure of risk aversion obtained for investor i for a portfolio choice at month t. Absolute Risk Aversion (ARA) is the risk aversion measure in columns 1 and 2, and Relative Risk Aversion (RRA) in columns 3 and 4. The right hand side variable is the (log) median house price in the investor's zip code at time t (and a quarter dummy in columns 2 and 4). Standard errors clustered at the investor level. *** indicates significance at the 1% levels of confidence.

Dependent Variable (in logs):	ARA		RRA	
	(1)	(2)	(3)	(4)
log (House Value)	-0.160***	-0.147***	0.184***	0.235***
	(0.0390)	(0.0380)	(0.0460)	(0.0480)
Quarter Dummies	No	Yes	No	Yes
Investor Fixed Effect	No	No	No	No
R-squared (adj)	0.019	0.046	0.010	0.082
Observations	2,354	2,354	2,354	2,354
Investors	1,378	1,378	1,378	1,378

Table 11: Risk Aversion and Wealth within Investor (Fixed Effects)

Elasticity of risk aversion to wealth for an investor, obtained through the following investor fixed effect estimation:

$$\ln(RiskAversion_{it}) = \alpha_i + \beta_1 \ln(HouseValue_{it}) + \delta_t + \omega_{it}$$

where the left hand side variable is the (log) measure of risk aversion obtained for investor i for a portfolio choice at month t. Absolute Risk Aversion (ARA) is the risk aversion measure in columns 1 and 2, and Relative Risk Aversion (RRA) in columns 3 and 4. The right hand side variables are the (log) median house price in the investor's zip code at time t and an investor dummy (and a quarter dummy in columns 2 and 4). Standard errors clustered at the investor level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Dependent Variable (in logs):	ARA		RRA	
	(1)	(2)	(3)	(4)
log (House Value)	-2.550**	-0.407	-4.815***	-4.188**
	(1.2470)	(1.3120)	(1.6130)	(1.7880)
Quarter Dummies	No	Yes	No	Yes
Investor Fixed Effect	Yes	Yes	Yes	Yes
R-squared (adj)	0.007	0.037	0.011	0.013
Observations	2,354	2,354	2,354	2,354
Investors	1,378	1,378	1,378	1,378

Table 12: Alternate Specification Test – Amount investment and Investment to Wealth Ratio

Cross sectional (within investor) elasticity of investment and investment/house price to wealth changes, estimated as in Table 11 (Table 12). Standard errors clustered at the investor level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Dependent Variable (in logs):	Investment		Investment/ House Value	
	(1)	(2)	(3)	(4)
log (House Value)	0.351***	5.096***	-0.649***	4.096**
	(0.062)	(1.620)	(0.062)	(1.620)
Investor Fixed Effect	No	Yes	No	Yes
R-squared (adj)	0.029	0.010	0.092	0.007
Observations	2,354	2,354	2,354	2,354
Investors	1,378	1,378	1,378	1,378

Table 13: Estimates from Automatic and Non-Automatic Buckets for the same Investment

Absolute Risk Aversion (ARA) and θ_0 obtained as in Table 6, 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. 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.

	θ_0			ARA		
	Non-Automatic Only	**Automatic Only**	**Difference**	**Non-Automatic Only**	**Automatic Only**	**Difference**
1. Full Sample						
Mean	1.080	1.079	0.001	0.0356	0.0368	-0.0012
sd	0.023	0.021	0.021	0.0194	0.0215	0.0204
Median	1.082	1.079	0.000	0.0402	0.0454	0.0003
N	227	227	227	227	227	227
2. Subsample: October-December 2007						
Mean	1.063	1.062	0.001	0.0340	0.0355	-0.0016
sd	0.019	0.013	0.017	0.0192	0.0235	0.0223
Median	1.060	1.059	0.000	0.0407	0.0469	0.0007
N	74	74	74	74	74	74
3. Subsample: January-April 2008						
Mean	1.089	1.087	0.002	0.0364	0.0374	-0.0011
sd	0.019	0.019	0.023	0.0195	0.0206	0.0195
Median	1.086	1.083	0.001	0.0402	0.0447	-0.0003
N	153	153	153	153	153	153

Table 14: Diversified Distance Test

For each loan we calculate the average distance between the borrower and the lenders' zip codes, weighted by the amount invested by each lender. We then classify each loan by month and risk bucket, and for each month we test whether the mean distance between any two possible buckets is statistically different from zero. The table reports the t-statistics for each month and risk buckets pair. The difference between buckets is not statistically different from zero in 122 out of 147 cases and there is no pattern for the months buckets for which it is significant (in bold).

Bucket:	A						B					C				D			E		F
minus:	B	C	D	E	F	G	C	D	E	F	G	D	E	F	G	E	F	G	F	G	G
2007m10	**2.26**	1.71	0.26	0.16	-1.10	0.52	-0.99	**-2.33**	**-2.36**	**-2.96**	-1.61	-1.78	-1.83	**-2.80**	-1.04	-0.13	-1.45	0.26	-1.32	0.36	1.40
2007m11	1.52	1.84	**3.22**	**2.66**	0.87	0.55	0.69	1.89	0.95	-0.40	-0.56	1.04	0.07	-0.81	-0.83	-1.28	-1.87	-1.83	-1.21	-1.30	-0.21
2007m12	-1.29	0.37	-0.80	-0.05	0.23	-0.09	1.92	0.76	1.45	1.09	0.88	-1.23	-0.47	-0.14	-0.32	0.82	0.78	0.52	0.23	-0.04	-0.25
2008m1	**3.59**	**3.08**	**3.39**	1.83	**2.15**	0.42	-0.29	-0.23	-1.76	-0.78	**-2.25**	0.07	-1.36	-0.50	-1.88	-1.67	-0.71	**-2.24**	0.77	-1.03	-1.47
2008m2	**3.95**	**2.67**	1.43	1.84	1.12	0.45	-1.01	-3.53	**-2.67**	**-2.18**	**-2.72**	**-2.03**	-1.37	-1.23	-1.76	0.63	0.15	-0.63	-0.35	-1.20	-0.79
2008m3	1.59	0.87	1.25	0.69	0.78	0.69	-0.87	-0.63	-1.69	-0.39	-0.65	0.40	-0.39	0.26	0.10	-1.20	0.03	-0.27	0.92	0.66	-0.30
2008m4	0.02	1.04	-0.66	0.05	0.24	0.56	1.96	-1.27	0.05	0.46	1.09	**-2.74**	**-2.06**	-0.85	-0.28	1.22	1.02	1.58	0.63	1.39	0.66