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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 investors' financial decisions in a person-to-person lending platform. We develop a method that obtains a risk-aversion parameter from each portfolio choice. Since the same individuals invest repeatedly, we construct a panel data set that we use to disentangle heterogeneity in attitudes toward risk across investors, from the elasticity of risk aversion to changes in wealth. We find that wealthier investors are more risk averse in the cross section and that investors become more risk averse after a negative housing wealth shock. Thus, investors exhibit preferences consistent with decreasing relative risk aversion and habit formation.

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1. Introduction

Theoretical predictions on investment, asset prices, and the cost of business cycles depend crucially on assumptions about the relationship between risk aversion and wealth.[1] Although characterizing this relationship has long been in the research agenda of empirical finance and economics, progress has been hindered by the difficulty of disentangling the shape of the utility function from preference heterogeneity across agents. For example, the bulk of existing work is based on comparisons of risk aversion across investors of different wealth, which requires assuming that agents have the *same* preference function. If agents have heterogeneous preferences, however, cross-sectional analysis leads to incorrect inferences about the shape of the utility function when wealth and preferences are correlated. Such a correlation may arise, for example, if agents with heterogeneous propensity to take risk make different investment choices, which in turn affect their wealth.[2] To characterize the properties of the joint distribution of preferences and wealth in the cross section, and to estimate the parameters describing the utility function, one needs to observe how the risk aversion of the same individual changes with wealth shocks.

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

The present paper exploits a novel environment to obtain, independently of wealth, unbiased measures of investor risk aversion and to examine the link between these estimates and investor wealth. We analyze the risk-taking behavior of 2,372 investors based on their actual financial decisions in Lending Club (LC), a person-to-person (P2P) lending platform in which individuals invest in diversified portfolios of small loans.[6] We develop a methodology to estimate the local curvature of an investor's utility function (absolute risk aversion, or ARA) from each portfolio choice. The key advantage of this estimation approach is that it does not require characterizing investors' outside wealth. We also exploit the fact that the same individuals make repeated investments in LC to construct a panel of risk-aversion estimates. We use this panel to both characterize the cross-sectional correlation between risk preferences and wealth and obtain reduced form estimates of the elasticity of investor-specific risk aversion to changes in wealth. We find the cross-sectional elasticity between RRA and wealth to be positive and the investor-specific wealth elasticities to be negative.

Our estimation method is derived from an optimal portfolio model where investors hold an unknown number of risky and riskless assets, including a portfolio of LC loans. We decompose the LC returns into a systematic component and an idiosyncratic return component orthogonal to the market. We use the idiosyncratic component to characterize investors' preferences: an investor's ARA is given by the additional expected return that makes that investor indifferent about allocating the marginal dollar to a loan with higher idiosyncratic default probability. Estimating risk preferences from the nonsystematic component of returns implies that the estimates are independent from the investors' overall risk exposure or wealth. Moreover, by measuring the curvature of the utility function directly from the first-order condition of this portfolio choice problem, we do not need to impose a specific shape of the utility function.

This method relies on two assumptions that we validate in the data. The first assumption is that LC loans are not held to simply replicate the market portfolio. This assumption is validated by the substantial heterogeneity of the mean and variance across investors' LC portfolios. The second assumption is that we can correctly capture investors' beliefs about the stochastic distribution of returns using the information provided on the LC's website. Although we cannot observe the investors' beliefs, we test this assumption indirectly by exploiting a feature of the LC environment: many investors choose LC loans both manually and through an optimization tool based on returns and default probabilities posted on the LC site. We use the sample of investors that use both methods to show that our estimate of investor-specific risk aversion obtained from the manually chosen component of their LC portfolio does not differ significantly from the estimate obtained from the component of the portfolio chosen with the tool. Testing the validity of assumptions concerning person-specific priors on idiosyncratic risk is typically impossible in real-life environments. Being able to validate our assumptions, although in an admittedly indirect way, represents an important advantage of this setting.

With this method we estimate parameters of risk aversion for each investor and portfolio choice in our sample. The average ARA implied by the trade-off between expected return and idiosyncratic risk in our sample of portfolio choices is 0.037. Our estimates imply an average income-based relative risk aversion (income-based RRA) of 2.81, with substantial unexplained heterogeneity and skewness.[7]

In estimating risk attitudes based on idiosyncratic risk, our approach is similar to that of the economic literature that studies risk attitudes and insurance choices (Cohen and Einav 2007, Barseghyan et al. 2013, Einav et al. 2012). Our estimates are also comparable to experimental measures of risk aversion, because investors in our model face choices similar to those faced by experimental subjects along important dimensions. Our model transforms a complex portfolio choice problem into a choice between well-defined lotteries of pure idiosyncratic risk, where returns are characterized by a discrete failure probability (i.e., default), and the stakes are small relative to total wealth (the median investment in LC is \$375).[8] The level, distribution, and skewness of the estimated risk-aversion parameters are similar to those obtained in laboratory and field experiments.[9] These similarities indicate that investors in our sample, despite being a self-selected sample of individuals who invest online, have risk preferences similar to individuals in other settings.

We show that our method generates consistent estimates for the curvature of the utility function under the expected utility framework and alternative preference specifications, such as loss aversion and narrow framing, as in Barberis and Huang (2001) and Barberis et al. (2006). This is a key feature of our estimation procedure, since under the expected utility framework, the observed high levels of risk aversion in small-stakes environments are difficult to reconcile with the observable behavior of agents in environments with larger stakes (Rabin 2000). We also show that our estimates of the elasticity of ARA with respect to investor wealth characterize agents' risk attitudes in both large- and small-stakes environments.

We exploit the panel dimension of our data to derive the cross-sectional and within-investor elasticities of risk aversion with respect to wealth. First, in the cross section, we find that wealthier investors exhibit lower ARA and higher RRA. Since we use imputed net worth as a proxy for wealth, our preferred specification corrects for measurement error in the wealth proxy using house prices in the investor's zip code as an instrument. We obtain an elasticity of ARA to wealth of −0.074, which implies a cross-sectional wealth elasticity of the RRA of 0.93.[10] These findings coincide qualitatively with Guiso and Paiella (2008) and Cicchetti and Dubin (1994), who also base their analysis on risk-aversion parameters estimated independently of their wealth measure.

Second, we estimate the elasticity of risk aversion to changes in wealth in an investor fixed-effect specification to characterize the shape of the utility function for the average investor. We use the decline in house prices in the investor's zip code during our sample period, October 2007 to April 2008, as a source of variation in investor wealth. The results indicate that the average investor's RRA increases after experiencing a negative housing wealth shock, with an estimated elasticity of −1.85. This is consistent with investors exhibiting decreasing relative risk aversion and with theories of habit formation (as in Campbell and Cochrane 1999) and incomplete markets (as in Guvenen 2009).[11]

The contrasting signs of the cross-sectional and within-investor elasticities confirm that investors have heterogeneous risk preferences that are correlated with wealth in the cross section. This implies that inference on the elasticity of risk aversion to wealth from cross-sectional data will be biased. In our setting, the bias implied by the joint distribution of preferences and wealth is large enough to flip the sign of the investor-specific risk-aversion elasticity to wealth.[12]

A novel feature of our estimation approach is that it disentangles the measurement of risk aversion from investors' assessments about the systematic risk of LC loans. On average, investors' perceived systematic risk premium in LC increases from 5.7% to 8.9% between the first and last months of the sample period. The increase in the perceived systematic risk is concurrent with the drop in house prices, which indicates that wealth shocks are potentially correlated with general changes in investors' beliefs. This calls for caution when using the share of risky assets as a measure of investor RRA. In our context, inference based on the share of risky assets alone would have led us to overestimate the investor-specific elasticity of risk aversion to wealth.

The rest of this paper is organized as follows. Section 2 describes the Lending Club platform. Section 3 illustrates 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.[13] 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. Social Security number 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 prespecified published rule posted on the website.[14] 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 three-year term with fixed interest rates and equal monthly installments and can be prepaid with no penalty for the borrower. When the loan is granted, the borrower pays a one-time fee to LC ranging from 1.25% to 3.75%, depending on the risk 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.[15] LC lowers the cost of investment diversification inside LC by providing an optimization tool that constructs the set of efficient loan portfolios for the investor's overall amount invested in LC, i.e., the minimum idiosyncratic variance for each level of expected return (see Figure 1).[16] In other words, the tool helps investors to process the information on interest rates and default probabilities posted on the website into measures of expected return and idiosyncratic variance that may otherwise be difficult to compute for an average investor (these computations are performed in Section 2.2).[17] When investors use the tool, they select, among all the efficient portfolios, the preferred one according to their own risk preferences. Investors can also use the tool's recommendation as a starting

Table 1. Borrower and Investor Characteristics

Variable	Mean	SD	Median
A—Borrower characteristics			
FICO score	694.3	38.2	688.0
Debt to income	0.128	0.076	0.128
Monthly income ($)	5,428	5,963	4,250
Amount borrowed ($)	9,224	6,038	8,000
B—Investor characteristics			
Male (%)	83		100
Age	43.4	15.0	40.0
Married (%)	56		100
Homeowner (%)	75		100
Net worth, imputed ($1,000's)	663.0	994.4	375.0
Median house value in zip code ($1,000's)	385.1	285.8	292.4
% Change in house price, 10/2007 to 04/2008 (%)	−4.08	4.97	−3.67

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

point and then make changes, or they can simply select the loans in their portfolio manually.

Of all portfolio allocations between LC's inception and June 2009, 39.6% was suggested by the optimization tool, 47.1% was initially suggested by the tool and then altered by the investor, and the remaining 13.3% was chosen manually.[18]

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

This subsection derives the expected return and variance of individual loans and risk buckets, following the same assumptions as the LC platform. All the loans in a given risk bucket $z = 1, \ldots, 35$ are characterized by the same scheduled monthly payment per dollar borrowed, P_z, over three years (36 monthly installments). The per-dollar scheduled payment P_z and the bucket-specific default rate π_z fully characterize the expected return and variance of *per-project* investments, μ_z and $1\sigma_z^2$.

LC considers a geometric distribution for the idiosyncratic monthly survival probability of the individual projects: the probability that the loan survives until month $\tau \in [1, 36]$ is $\Pr(T = \tau) = \pi_z(1-\pi_z)^\tau$.[19] The resulting expectation and variance of the present value of the payments, P_z, of any project in bucket z are

$$\mu_z = P_z\left[1 - \left(\frac{1-\pi_z}{1+r}\right)^{36}\right]\frac{1-\pi_z}{r+\pi_z},$$

$$\sigma_z^2 = \sum_{t=1}^{35} \pi_z(1-\pi_z)^t \left(\sum_{\tau=1}^{t} \frac{P_z}{(1+r)^\tau}\right)^2 + \left(\sum_{\tau=1}^{36} \frac{P_z}{(1+r)^\tau}\right)^2 (1-\pi_z)^{36} - \mu_z^2,$$

where r is the risk-free interest rate.

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:

$$\mathrm{var}[r_z^i] = \frac{\sigma_z^2}{n_z^i}, \tag{1}$$

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

Then, the variance of the return on investment in bucket z can be decomposed as follows:

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

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

The expected return of an investment in bucket z is not affected by the number of loans in the investor's portfolio; it is equal to the expected return on a loan in bucket z, μ_z, and is constant across investors:[20]

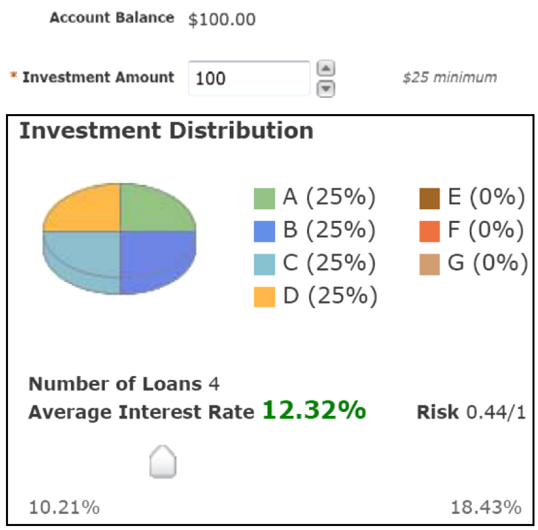
$$E[R_z] = E[R_z^i] = \mu_z. \tag{2}$$

3. Estimation Procedure

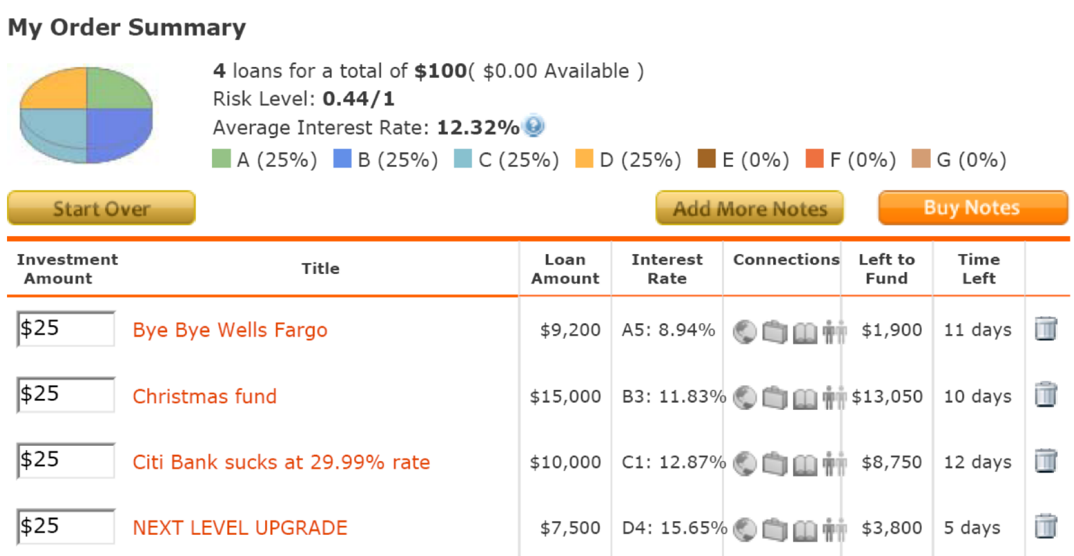
To capture the fact that most individuals invest not only in the market and the risk-free asset but also in individual securities, our framework considers investors that, instead of simply holding a replica of the market portfolio, also hold securities based on their own subjective *insights* that they will generate an excess return. The decision to invest in LC depends on investors' knowledge of its existence and their subjective expectation that LC is, indeed, a good investment opportunity. Thus, it is reasonable to assume that investors in LC have special insights, which explains why, as we show later, their portfolio departs from just replicating the market.[21]

Figure 1. (Color online) Portfolio Tool Screen Examples for a $100 Investment

A. Screen 1: Interest rate—normalized variance "Slider"



B. Screen 2: Suggested portfolio summary



Notes. 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 (panel A). 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 0 and 1). Once a portfolio has been formed, a new screen shows the loan composition of the investor's portfolio, including each individual loan (panel B). In this screen the investor can change the amount allocated to each loan, drop them altogether, or add others.

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

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

We test the assumptions on investors' beliefs in Section 5, i.e., that they act as if there is a common systematic factor and that the choice of LC loans does not simply replicate the market portfolio. The data strongly support both hypotheses.

3.1. The Model

Each investor i chooses the share of wealth to be invested in $z = 1, \ldots, Z$ securities with return R_z and $Z \geq 35$. We consider securities $z = 1, \ldots, 35$ to represent the LC risk buckets. We explicitly include outside investment options, $z = 36, \ldots, Z$, that represent the market composite, a risk-free asset, real estate, human capital, and other securities potentially unknown to the econometrician.

A projection of the return of each security against that of the market, R_m, gives two factors. The first is the systematic return of the security, and the second, its independent return:

$$R_n^i = \beta_n^i \cdot R_m + r_n^i. \tag{3}$$

We assume that all LC risk buckets have the same systematic risk, and we allow the prior about such systematic component, β_L^i, to be investor specific—that is, for all $z = 1, \ldots, 35$:$\beta_z^i = \beta_L^i$. We test and validate empirically this assumption in Section 5.2.[22]

The assumption that all risk buckets have the same systematic risk is combined with the Sharpe diagonal model, which assumes that the returns on the LC loans are related to other securities and investment opportunities only through their relationships with a common underlying factor, and thus the independent returns, defined in Equation (3), are uncorrelated. When we allow a time dimension, the independent returns are also uncorrelated across time. This feature of the model is exploited in Section 6.2, when we analyze multiple investment by the same agent.

Assumption 1 (Sharpe Diagonal Model).

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

An example of an underlying common factor is an increase in macroeconomic risk (i.e., financial crisis) triggering correlated defaults across buckets. In our setting, such a common factor is reflected in the systematic component of Equation (3) and can vary across investors and over time.

Each investor i faces the following portfolio choice problem:

$$\max_{\{x_z\}_{z=1}^{Z}} \; Eu\left(W^i\left[\sum_{z=1}^{Z} x_z^i R_z^i\right]\right)$$
$$\text{s.t.} \quad \sum_{z=1}^{Z} x_z = 1,$$
$$x_z = 0 \text{ or } x_z \geq 25 \quad \text{for all } z = 1, \ldots, 35;$$

$\{x_z\}_{z=1}^{Z}$ correspond to the shares of the wealth, W_i, invested in each security z.

The first-order condition characterizing the optimal portfolio share of any LC bucket $z = 1, \ldots, 35$ is

$$foc(x_z): \quad E[u'(c_i) \cdot W^i \cdot R_z] - \mu^i - \lambda_h^i (x_z > 25) = 0,$$

where μ^i corresponds to the multiplier on the budget constraint, $\sum_z^Z x_z = 1$, and λ_z^i is the Kuhn–Tucker multiplier on the minimum LC investment constraint, which is 0 for all those buckets for which the investor has a positive position.

For all buckets with $x_z \geq 25$, a first-order linearization on the first-order condition around expected consumption results in the following optimality condition for all buckets with positive investment:

$$foc(x_z): \quad u'(E[c^i])W^i E[R_z^i] + u''(E[c^i])(W^i)^2 \cdot \left(\sum_{z'=1}^{Z} x_{z'}^i \operatorname{cov}[R_{z'}^i, R_z^i]\right) - \mu^i = 0. \tag{4}$$

Because of the \$25 minimum investment per loan constraint, this first-order condition characterizes the optimal portfolio shares in those risk buckets where there is an interior solution, e.g., where the investor chooses a positive and finite investment amount. In other words, this optimality condition describes the investment share that makes the investor indifferent about allocating an additional dollar to a loan in bucket z when investment in the bucket is greater than 0.[23] By contrast, in corner solutions where the additional expected return is always smaller (larger) than the marginal increase in risk for any investment amount larger than \$25, investment in that bucket will be 0 (infinity). We describe in detail the optimality condition that characterizes interior and corner solutions in Online Appendix B.

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

$$\forall z \in \{1, \ldots, 35\} \wedge \forall h \in \{36, \ldots, Z\}: \quad \operatorname{cov}[R_z^i, R_h^i] = \beta_L^i \beta_h^i \operatorname{var}[R_m],$$
$$\forall z, z' \in \{1, \ldots, 35\}, z \neq z': \quad \operatorname{cov}[R_z^i, R_{z'}^i] = (\beta_L^i)^2 \operatorname{var}[R_m],$$
$$\forall z \in \{1, \ldots, 35\}: \quad \operatorname{cov}[R_z^i, R_z^i] = (\beta_L^i)^2 \operatorname{var}[R_m] + \operatorname{var}[r_z^i],$$

where β_L^i is the market sensitivity, or *beta*, of the LC returns, defined in Equation (3) and assumed constant across buckets; and β_h^i is the corresponding sensitivity for the investor's outside security h. The variance of any risk bucket z is given by its systematic component, $V_z^i = (\beta_L^i)^2 \operatorname{var}[R_m]$, and its idiosyncratic risk, derived in Equation (1): $\operatorname{var}[r_z^i] = \sigma_z^2 / n_z^i$.

Rearranging terms, we derive our main empirical equation. For all LC risk buckets $z = 1, \ldots, 35$ for which investor i has a positive position,

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

where

$$\theta^i \equiv \frac{\mu^i}{W^i u'(E[c^i])} + ARA^i W^i \beta_L^i \mathrm{var}[R_m] \cdot \left(\beta_L^i \sum_{z'=1}^{35} x_{z'}^i + \sum_{z'=36}^{Z} \beta_{z'}^i x_{z'}^i\right), \tag{6}$$

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

The parameter θ^i reflects the investor's assessment of the systematic component of the LC investment.[24] It is investor and investment specific, and constant across buckets for each investment. The parameter ARA^i corresponds to the absolute risk aversion. It captures the extra expected return needed to leave the investor indifferent when taking extra risk. Such parameter refers to the local curvature of the preference function, and it is not specific to the expected utility framework. We show in Online Appendix A that the same equation characterizes the optimal LC portfolio and the curvature of the utility function under two alternative preference specifications: (1) when investors are averse to losses in their overall wealth and (2) when investor utility depends in a nonseparable way on both the overall wealth level and the income flow from specific components of the portfolio (narrow framing).

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. The holding of a portfolio of securities outside LC, which includes market systematic fluctuation, optimally adjusts to account for the indirect market risk embedded in LC.[25]

Finally, we cannot compute the RRA without observing the expected lifetime wealth of the investors.[26] However, for the purpose of comparing our estimates with the results from other empirical studies on relative risk aversion, we follow that literature and define the relative risk-aversion parameter based solely on the income generated by investing in LC (see, for example, Holt and Laury 2002). This *income-based RRA* is defined as follows:

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

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

4. Data and Sample

Our sample covers the period between October 2007 and April 2008. Below we provide summary statistics of the investors' characteristics and their portfolio choices, as well as 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 specializing in recovering consumer demographics. Acxiom uses a proprietary algorithm to recover gender from the investor names, and it matches investor names and home addresses to available public records to recover age, marital status, home ownership status, and an estimate of net worth. Such information is available at the beginning of the sample.

Table 1, panel B shows the demographic characteristics of the LC investors. The average investor in our sample is 43 years old, 8 years younger than the average respondent in the Survey of Consumer Finances (SCF). As expected from younger investors, the proportion of married participants in LC (56%) is lower than in the SCF (68%). Men are overrepresented among participants in financial markets and account for 83% of the LC investors; similarly, the faction of male respondents in the SCF is 79%. In terms of income and net worth, investors in LC are comparable to other participants in financial markets, who are typically wealthier than the median U.S. households. The median net worth of LC investors is estimated between \$250,000 and \$499,999, significantly higher then the median U.S. household (\$120,000 according to the SCF) but similar to the estimated wealth of other samples of financial investors. Korniotis and Kumar (2011), for example, estimate the wealth of clients in a major U.S. discount brokerage house in 1996 at \$270,000.

To obtain an indicator of housing wealth, we match investors' information with the Zillow Home Value Index by zip code. The Zillow Index for a given geographical area is the value of the median property in that location, estimated using a proprietary hedonic model based on house transactions and house characteristics data, and it is available at a monthly frequency. LC investors are geographically dispersed but tend to be concentrated in urban areas and major cities. Table 1 shows the descriptive statistics of median house values on October 2007 and their variation during the sample period, October 2007 to April 2008.

4.2. Sample Construction

We consider as a single portfolio choice all the investments an individual makes within a calendar month.[27] The full sample contains 2,168 investors and 5,191

Table 2. Descriptive Statistics

	(1) All investments			(2) Diversified investments			(3) With real estate data		
Sample/subsample	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
		A—Unit of observation: Investor-bucket-month							
		($N = 50{,}254$)			($N = 43{,}662$)			($N = 38{,}980$)	
Investment ($)	302.8	2,251.4	50.0	86.0	206.9	50.0	88.4	215.1	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	2.96	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 $1 *investment*)	0.036	0.020	0.035	0.027	0.020	0.022	0.027	0.020	0.022
		B—Unit of observation: Investor-month							
		($N = 5{,}191$)			($N = 3{,}745$)			($N = 3{,}294$)	
Investment	2,932	28,402	375	1,003	2,736	375	1,044	2,864	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	23.7	29.3	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*)	0.012	0.016	0.005	0.005	0.007	0.003	0.005	0.006	0.002

Notes. Each observation in panel A represents an investment allocation, with at least two risk buckets, by investor i in risk bucket z in month t. In panel B, each observation represents a portfolio choice by investor i in month t. An investment constitutes a dollar amount allocation to projects (requested loans), classified in 35 risk buckets, within a calendar month. Loan requests are assigned to risk buckets according to the amount of the loan, the FICO score, and other borrower characteristics. Lending Club assigns and reports the interest rate and default probability for all projects in a bucket. The expectation and variance of the present value (PV) of $1 investment in a risk bucket is calculated assuming a geometric distribution for the idiosyncratic monthly survival probability of the individual loans and independence across loans within a bucket. The sample in column (2) excludes portfolio choices in a single bucket and nondiversified 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.

portfolio choices, which results in 50,254 investment-bucket observations. To compute the expected return and idiosyncratic variance of the investment-bucket in Equations (1) and (2), we use as the risk free interest rate the three-year yield on Treasury bonds at the time of the investment. Table 2, panel A reports the descriptive statistics of the investment-buckets. The median expected return is 12.2%, with an idiosyncratic variance of 3.5%. Panel B describes the risk and return of the investors' LC portfolios. The median portfolio expected return in the sample is 12.1%, almost identical to the expectation at the bucket level, but the idiosyncratic variance is substantially lower, 0.005%, because of 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 forgo 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 by the econometrician, such deviations from full diversification will bias the risk-aversion estimates downward. To avoid such bias, we exclude all nondiversified 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, whereas the idiosyncratic variance in the analysis sample is smaller. This is expected since the analysis sample excludes nondiversified investment components.

In the wealth analysis, we further restrict the sample to those investors that are located in zip codes where the Zillow Index is computed. This reduces the sample to 2,061 investors and 3,405 portfolio choices. This final selection does not alter the observed characteristics of the portfolios significantly (see 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:

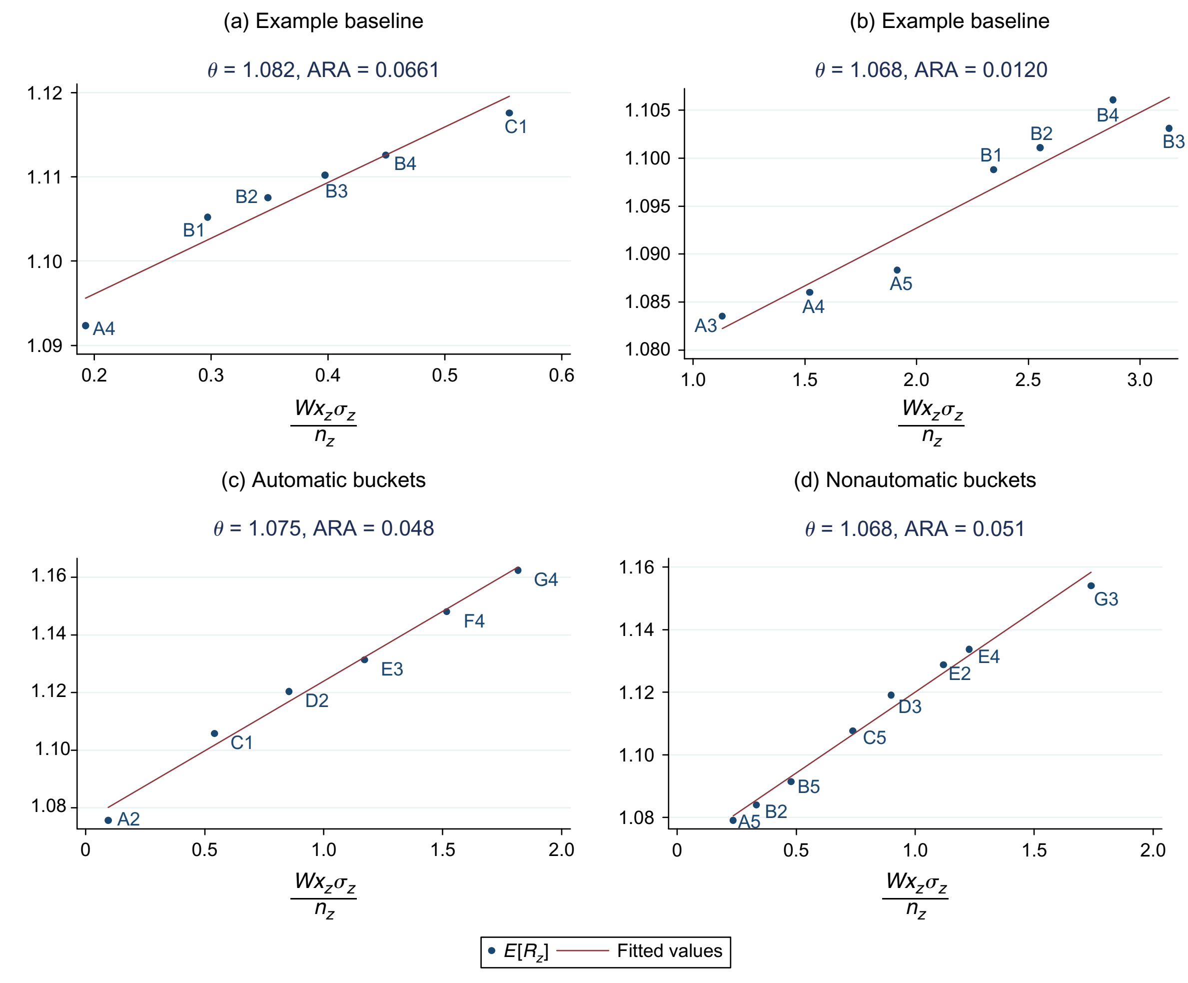
$$E[R_z] = \theta^i + ARA^i \cdot \frac{W^i x_z^i}{n_z^i} \cdot \sigma_z^2 + \varepsilon_z^i. \tag{9}$$

There is one independent equation for each bucket z with a positive investment in the investor's portfolio. The median portfolio choice in our sample allocates funding to 10 buckets, which provides us with multiple degrees of freedom for estimation. We estimate the parameters of Equation (9) with ordinary least squares.

Panels (a) and (b) in Figure 2 show two examples of portfolio choices. The vertical axis measures the expected return of a risk bucket, $E[R_z]$, and the horizontal axis measures the bucket variance weighted by the investment amount, $W^i x_z^i \sigma_z^2 / n_z^i$. The slope of the linear fit is our estimate of the absolute risk aversion, and it is reported on the top of each plot.

The error term captures deviations from the efficient portfolio as a result of measurement errors by investors, and real or perceived private information. 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.

Figure 2. (Color online) Examples of Risk Return Choices and Estimated ARA



Notes. Plots (a) and (b) represent examples of two different investments 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 ARA. The intersection of this linear fit with the vertical axis is our estimate for the risk premium (θ). Plots (c) and (b) represent allocations to risk buckets of the *same* actual investment. Panel (c) shows the buckets that were chosen by the portfolio tool (*Automatic*), and panel (d) shows buckets directly chosen by the investor (*Nonautomatic*).

5.1. Results

The descriptive statistics of the estimated parameters of Equation (9) for each portfolio choice are presented in Table 3. The average estimated ARA across all portfolio choices is 0.037 (column (1)). Investors exhibit substantial heterogeneity in risk aversion, and its distribution is left skewed: the median ARA is 0.044 and the standard deviation is 0.0245. 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 (2012), we can recover the variance of the true ARA by subtracting the expected estimation variance across all portfolio choices. The calculated standard deviation of the true ARA is 0.0226, indicating that the estimation variance is small relative to the variance of risk aversion across investments.[28] The range of the ARA estimates is consistent with the estimates recovered in the laboratory. Holt and Laury (2002), for example, obtain ARA estimates between 0.003 and 0.109, depending on the size of the bet.

The experimental literature often reports the income-based RRA, defined in Equation (8). To compare our results with those of laboratory participants, we report the distribution of the implied income-based RRA in Table 3, column (4). The mean income-based RRA is 2.81, and its distribution is right skewed (median of 1.62). This parameter scales the measure of absolute risk aversion according to the lottery expected income; therefore, it mechanically increases with the size of the bet. Column (3) of Table 3 reports the distribution of expected income from LC. The mean expected income is \$125.6, substantially higher than the bet in most laboratory experiments. Not surprisingly, although the computed ARA in experimental work is typically larger than our estimates, the income-based RRA parameter is smaller, ranging from 0.3 to 0.52 (see, for example, Chen and Plott 1998; Goeree et al. 2002, 2003; and Goeree and Holt 2004). Our results are comparable to Holt and Laury (2002), who also estimate risk aversion for agents facing large bets and (implicitly) find income-based RRA similar to ours, 1.2. Finally, Choi et al. (2007) report risk premia with a mean of 0.9, which corresponds to an income-based RRA of 1.8 in our setting. That paper also finds right skewness in their measure of risk premia.

Our findings imply that the high levels of risk aversion exhibited by subjects in laboratory experiments extrapolate to actual small-stakes investment choices. Rabin and Thaler (2001, 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. Our results are subject to that critique. The median RRA computed with our estimates of ARA and investors' net worth is 8,858 (average is 26,317).[29] This suggests that the expected utility framework on overall wealth cannot describe agents' behavior in our environment. We show in Online Appendix A that the ARA estimated here describes the curvature of the utility function in other preference frameworks that are consistent with observed risk behavior over small- and large-stakes gambles. In particular, Online Appendix A.1 describes the optimal portfolio choice in a behavioral model in which utility depends (in a nonseparable way) on both overall wealth level, W, and the flow of income from specific components of the agent's portfolio, y.[30] In such alternative preference specifications, agents' ARA varies with both the level of overall wealth and the income flow generated by the gamble. This implies that the estimated *level* of ARA may be larger for small-stakes gambles (i.e., $\partial ARA(y,W)/\partial y < 0$). Nevertheless, the *elasticity* of ARA with respect to investor's wealth (i.e., $(\partial ARA(y,W)/\partial W)(W/ARA(y,W))$), our focus in the next section, is consistent in small- and large-stakes environments.

Column (2) in Table 3 shows the estimates of the parameter θ, defined in Equation (6), which captures 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, or any potential risk of the lending platform common to all risk buckets. The average estimated θ is 1.086, which indicates that the average

Table 3. Unconditional Distribution of Estimated Risk-Aversion Parameters

	(1) ARA	(2) θ	(3) Expected income	(4) Income-based RRA
Mean	0.03706	1.086	125.6	2.81
SD	0.02450	0.028	327.3	3.54
$p1$	−0.00812	1.045	4.1	−0.16
$p10$	0.01177	1.059	8.2	0.29
$p25$	0.02293	1.076	16.0	0.56
$p50$	0.04404	1.086	45.5	1.61
$p75$	0.04813	1.094	107.8	3.59
$p90$	0.05300	1.104	292.1	7.16
$p99$	0.08675	1.156	1,226.4	16.79
N	3,286	3,286	3,286	3,286

Notes. The ARA and intercept θ are obtained through the OLS estimation of the following relationship for each investment:

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

where the left-hand-side (right-hand-side) variable is the expected return (idiosyncratic variance times the investment amount) of the investment in bucket z. The income-based RRA is the estimated ARA times the total expected income from the investment in Lending Club. The Nth percentile of the distribution is denoted by pN.

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 of 3%) when compared with the variation in the ARA estimates (coefficient of variation of 66%).[31] Note that our ARA estimates are not based on this systematic risk premium; instead, they are based on the marginal premium required to take an infinitesimally greater idiosyncratic risk.

Table 4 presents the average and standard deviation of the estimated parameters by month. The average ARA increases from 0.029 during the first three months, to 0.039 during the last three (column (1)). This average time-series variation is potentially due to heterogeneity across investors as well as within-investor variation, since not all investors participate in LC every month. The analysis in the next section disentangles the two sources of variation.

The estimated θ's, shown in column (2), imply that the average systematic risk premium increases from 5.7% to 8.9% between the first and last three months of the sample period. Note that the LC website provides no information on the systematic risk of LC investments. Thus, this change is solely driven by changes in investors' beliefs about the potential systematic risk of the lending platform—that is, the correlation between the likelihood of default of LC loans and aggregate macroeconomic shocks (covariance between LC returns and market returns, β_L), or about the expected market risk premium ($E[R_m]$), or about the functioning of the platform. This pattern indicates that wealth shocks are potentially correlated with changes in investors' beliefs about risk and return on financial assets. Thus, we cannot infer the elasticity of RRA to wealth by observing changes in the share of risky assets after a wealth shock, as they may be simply reflecting changes in beliefs about the underlying distribution of risky returns. Our proposed empirical strategy in the next section overcomes this identification problem.

Table 4. Mean Risk Aversion and Systematic Risk Premium by Month

	(1) ARA	(2) θ	(3) Expected income	(4) Income-based RRA
2007m10	0.029	1.057	173.411	1.292
	(0.020)	(0.013)	(603.8)	(1.054)
2007m11	0.033	1.064	110.913	1.208
	(0.018)	(0.013)	(333.3)	(0.946)
2007m12	0.037	1.066	77.858	1.442
	(0.016)	(0.013)	(193.3)	(1.506)
2008m1	0.036	1.083	171.576	2.790
	(0.031)	(0.038)	(496.4)	(3.636)
2008m2	0.040	1.089	116.564	3.123
	(0.022)	(0.017)	(275.2)	(3.791)
2008m3	0.037	1.097	139.392	3.752
	(0.025)	(0.026)	(269.2)	(4.197)
2008m4	0.039	1.089	61.579	1.932
	(0.027)	(0.023)	(107.3)	(2.209)

Notes. The ARA and intercept θ are obtained through the OLS estimation of the following relationship for each investment:

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

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

5.2. Belief Heterogeneity and Bias: The Optimization Tool

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

The parameter θ will not capture the heterogeneity of beliefs that affects the relative risk and expected return across buckets. This is the case if investors believe that the market sensitivity of returns is different across LC buckets, i.e., if $\beta_z^i \neq \beta_L^i$ for some $z = 1, \ldots, 35$; 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 $z = 1, \ldots, 35$. In such cases, the equation characterizing the investor's optimal portfolio is given by

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

This expression differs from our main specification Equation (5) in three bias terms: $B_\sigma \equiv (\sigma_z^i/\sigma_z)^2$, $B_\mu \equiv (E[R_z] - E^i[R_z])/(W^i x_z^i \sigma_z^2/n_z^i)$, and $B_\beta \equiv (\beta_z^i - \beta_L^i)/(W^i x_z^i \sigma_z^2/n_z^i)$.

Two features of the LC environment allow us to estimate the magnitude of the overall bias from these sources. First, LC posts on its website an estimate of the idiosyncratic default probabilities for each bucket. Second, LC offers an optimization tool to help investors to diversify their loan portfolio. The tool constructs the set of efficient loan portfolios, given the investor's total amount in LC—i.e., the minimum idiosyncratic variance for each level of expected return. Investors then select, among all the efficient portfolios, the preferred one according to their own risk preferences. Importantly, the tool uses the same modeling assumptions regarding investors' beliefs that we use in our framework: the idiosyncratic probabilities of default are the ones posted on the website and the systematic risk is common across buckets; i.e., $\beta_z = \beta_L$.[32]

Thus, we can measure the estimation bias by comparing, for the *same* investment, the ARA estimates obtained independently from two different components of the portfolio choice: the loans suggested by the tool and those chosen manually. If investors' beliefs do not deviate systematically across buckets from the information posted on LC's website and from the assumptions of the optimization tool, we should find investor preferences to be consistent across the two measures. Note that our identification assumption does not require that investors agree with LC assumptions. It suffices that the difference in beliefs does not vary systematically across buckets. For example, our estimates are unbiased if investors believe that the idiosyncratic risk is 20% higher than the one implied by the probabilities reported in LC, across all buckets. Note, moreover, that our test is based on investors' beliefs at the time of making the portfolio choices. These beliefs need not to be correct ex post.

For this test we use the subsample of investments that combine buckets chosen through the optimization tool with buckets chosen manually. Then, 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 (nonautomatic buckets). Panels (c) and (d) in Figure 2 provide an example of this estimation. Both panels plot the expected return and weighted idiosyncratic variance for the *same* portfolio choice. Panel (c) includes only the automatic buckets, suggested by the optimization tool. Panel (d) includes only the nonautomatic buckets, chosen directly by the investor. The estimated ARAs using the automatic and nonautomatic 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 nonautomatic buckets. To verify that investments that contain an automatic component are representative of the entire sample, we compare the extreme cases where the entire portfolio is suggested by the tool and those where the entire portfolio is chosen manually. The median ARA values are 0.0455 and 0.0446, 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 automatic and nonautomatic components is representative of the entire investment sample.

Table 5, panel A reports the descriptive statistics of the ARA and θ estimated using the automatic and the nonautomatic buckets. The average ARA is virtually

Table 5. Estimates from Automatic and Nonautomatic Buckets

	(1) ARA	(2)	(3) θ	(4)
	Mean	SD	Mean	SD
A—Full sample ($n = 243$)				
Automatic	0.0373	0.0213	1.079	0.0205
Nonautomatic	0.0360	0.0194	1.080	0.0221
Automatic − Nonautomatic	−0.0014	0.0202	0.001	0.0209
B—Subsample: Oct–Dec 2007 ($n = 76$)				
Automatic	0.0357	0.0232	1.061	0.0134
Nonautomatic	0.0336	0.0190	1.063	0.0191
Automatic − Nonautomatic	−0.0021	0.0221	0.001	0.0167
C—Subsample: Jan–Apr 2008 ($n = 167$)				
Automatic	0.0381	0.0204	1.086	0.0183
Nonautomatic	0.0371	0.0195	1.088	0.0187
Automatic − Nonautomatic	−0.0010	0.0194	0.001	0.0226

Notes. Descriptive statistics of the 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 nonautomatic (buckets chosen directly by investor) bucket choices for the same investment. The table reports the mean and standard deviation of both estimates and of the difference for the *same* investment for the full sample and for 2007 and 2008 separately.

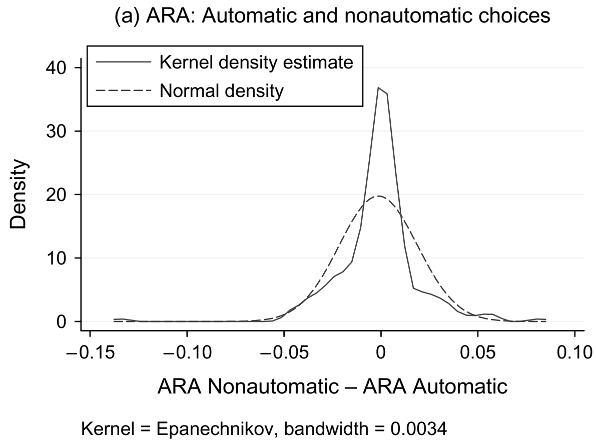
identical across the two estimations (see Table 5, columns (1) and (2)). Figure 3, panel (a) shows the entire distribution of this difference. The mean is 0 and the distribution of the difference is concentrated around 0, with kurtosis of 11.53. This implies that the bias is close to 0 not only in expectation but investment by investment.

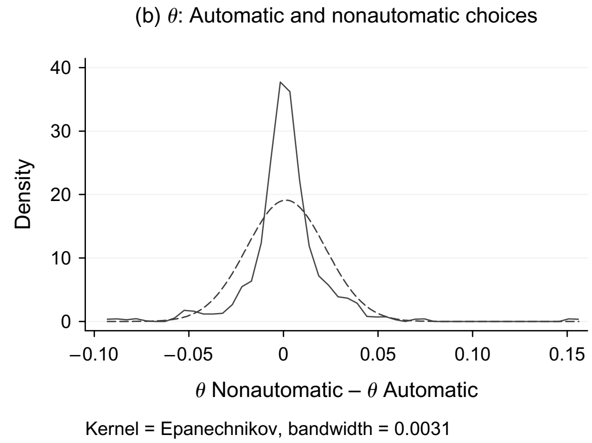
These results suggest that investors' beliefs about the stochastic properties of the loans in LC do not differ substantially from those posted on the website. They also suggest that investors' choices are consistent with the assumption that the systematic component is constant across buckets. Overall,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

In Table 5, panels B and C, we show that the difference in the distribution of the estimated ARA from the automatic and nonautomatic buckets is insignificant during both the first and second halves of the sample period. This 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 house prices. Although we cannot directly rule out that changes in house prices are correlated with changes in beliefs for the same investor, we find that beliefs remain consistent with our assumptions in expectation throughout the sample period.

Columns (3) and (4) of Table 5 show that the estimated risk premia, θ, also exhibit almost iden-

Figure 3. Investment-by-Investment Bias Distribution





Notes. Shown is a subsample of investments that combine buckets chosen through the optimization tool (Automatic) with buckets chosen manually (Nonautomatic). The figures plot the distribution of the difference between the estimates of ARA and θ obtained using nonautomatic and automatic buckets separately, for the same investment. For comparison, the figures include a Normal distribution with the corresponding standard deviation.

tical mean and standard deviations when obtained independently using the automatic and nonautomatic investment components. Figure 3, panel (b) shows the distribution of the difference between the two estimates of θ for the same investment. This suggests that our estimates of the risk premium are unbiased.

It is worth reiterating that these findings do not imply that investors' beliefs about the overall risk of investing in LC do not change during the sample period. On the contrary, the observed average increase in the estimated systematic risk premium in Table 4 is also observed in panels B and C of Table 5: θ increases by 2.5 percentage points between the first and second halves of the sample. The results in Table 5 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.

6. Risk Aversion and Wealth

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

$$\xi_{RRA,W} = \xi_{ARA,W} + 1, \tag{10}$$

where $\xi_{RRA,W}$ and $\xi_{ARA,W}$ refer to the wealth elasticities of RRA and ARA, respectively. For robustness, we also estimate the elasticity of the income-based RRA in Equation (8), $\xi_{\rho,W}$.

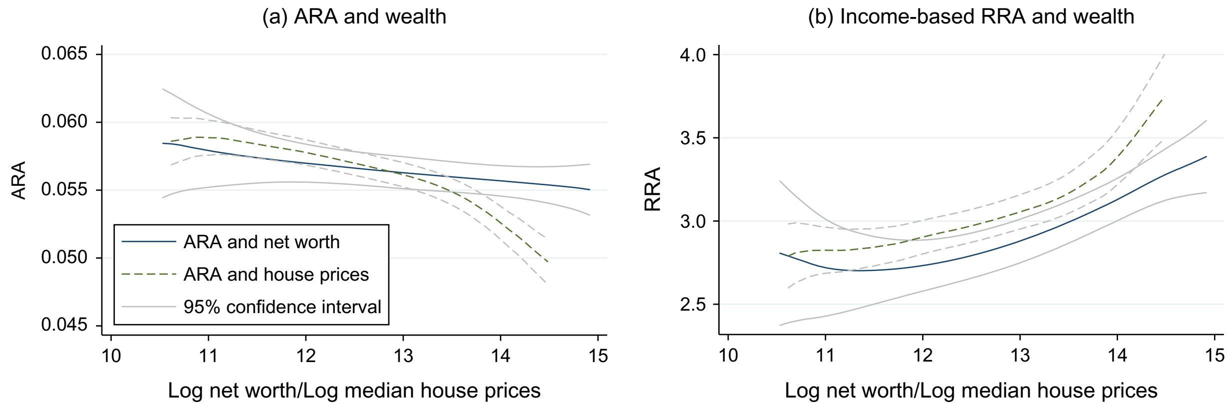
We exploit the panel dimension of our data and estimate these elasticities both in the cross section of investors and, for a given investor, in the time series. In the cross section, wealthier investors exhibit lower ARA and higher RRA when choosing their portfolio of loans within LC; we refer to these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

Below, we describe our proxies for wealth in the cross section of investors, and for wealth shocks in the time series. Since the bulk of the analysis uses housing wealth as a proxy for investor wealth, we focus the discussion in this section on the subsample of investors that are homeowners.[33]

6.1. Cross-Sectional Evidence

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

Figure 4. (Color online) Risk Aversion and Wealth in the Cross Section



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

We begin by exploring nonparametrically the relationship between the risk-aversion estimates and our two wealth proxies for the cross section of homeowner investors in our sample. Figure 4 plots a kernel-weighted local polynomial smoothing of the risk-aversion measure. The horizontal axis measures the (log) net worth and the (log) median house price in the investor's zip code at the time of the portfolio choice. ARA is decreasing in both wealth proxies while income-based RRA is increasing.

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

$$\ln(ARA_i) = \beta_0 + \beta_1 \ln(NetWorth_i) + \omega_i. \tag{11}$$

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

To account for measurement error in our wealth proxy, we estimate specification (11) in an errors-in-variables model by instrumenting imputed net worth with the average (log) house value in the zip code of residence of investor i during the sample period. Since the instrument varies only at the zip code level, in the estimation we allow the standard errors in specification (11) to be clustered by zip code. The errors-in-variables approach works in our setting because risk preferences are obtained independently from wealth. If, for example, risk aversion were estimated from the share of risky and riskless assets in the investor portfolio, this estimate would inherit the errors in the wealth measure. As a result, any observed correlation between risk aversion and wealth could be spuriously driven by measurement errors. This is not a concern in our exercise.

Table 6 shows the estimated cross sectional elasticities with OLS and the errors-in-variables model. Our preferred estimates from the errors-in-variables model indicate that the elasticity of ARA to wealth in the cross section is −0.074 and statistically significant at the 1% confidence level (column (2)). The nonparametric relationship is confirmed: wealthier investors exhibit a lower ARA. The OLS elasticity estimate is biased toward 0. This attenuation bias is consistent with classical measurement error in the wealth proxy.

The estimated ARA elasticity and Equation (10) imply that the wealth-based RRA elasticity to wealth is positive, $\widehat{\xi}^{xs}_{RRA,W} = 0.93$. Columns (3) and (4) of Table 6 show the result of estimating specification (11) using the income-based RRA as the dependent variable. The income-based RRA increases with investor wealth in the cross section, and the point estimate, 0.078, is also significant at the 1% level (column (4)). The sign of the estimated elasticity coincides with that implied by the ARA elasticity. Overall, the results consistently indicate that the RRA is larger for wealthier investors in the cross section.

6.2. Within-Investor Estimates

The above elasticity, obtained from the variation of risk aversion and wealth in the cross section, can be taken to represent the form of the utility function of the representative investor only under strong assumptions, i.e., when the distributions of wealth and preferences in the population are independent.[34] To identify the functional form of individual risk preferences, we estimate the ARA elasticity using within-investor time-series variation in wealth.

House values dropped sharply during our sample period.[35] Since housing represents a substantial fraction of household wealth in the United States, this

Table 6. Risk Aversion and Wealth, Cross-Section Estimates

DV (in log):	(1) ARA	(2) ARA	(3) Income-based RRA	(4) Income-based RRA	(5) log(*NetWorth*)
	OLS	Errors-in-var.	OLS	Errors-in-var.	First stage
log(*NetWorth*)	−0.010**	−0.074***	0.020**	0.078***	
	(0.004)	(0.021)	(0.008)	(0.029)	
log(*HouseValue*)					1.327***
					(0.120)
R^2	0.003		0.004		0.068
Observations (investors)	1,794	1,794	1,791	1,791	1,794

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

*, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

decline implied an important negative wealth shock for homeowners.[36] We use this source of variation to estimate the wealth elasticity of investor-specific risk aversion in the subsample of homeowners that invest in LC:

$$\ln(ARA_{it}) = \alpha_i + \beta_2 \ln(HouseValue_{it}) + t + \omega_{it}. \quad (12)$$

The left-hand-side variable is the estimated ARA for investor i in month t. The right-hand-side variable of interest is the (log) median house value of the investor's zip code during the month the risk-aversion estimate was obtained (i.e., the month the investment in LC takes place). The right-hand side of specification (12) includes a full set of investor dummies as controls. These investor fixed effects (FE) account for all cross-sectional differences in risk-aversion levels. Thus, the elasticity β_2 recovers the sensitivity of ARA to investor-specific shocks to wealth. We also include a time trend to absorb the evolution of housing prices, common to all investors, during the period under analysis.

By construction, the parameter β_2 can be estimated only for the subsample of investors that choose an LC portfolio more than once in our sample period. Although the average number of portfolio choices per investor is 2.0, the median investor chooses only once during our analysis period. This implies that the data over which we obtain the within-investor estimates using (12) come from approximately half of the original sample. To ensure that the results below are representative of the full investor sample, we also show the results of estimating specification (12) without the investor FE to corroborate that the conclusions of the previous section are unchanged when estimated on the subsample of investors that chose portfolios more than once and controlling for time trends.[37]

Table 7 reports the parameter estimates of specification (12), before and after including the investor FE. The FE results represent our estimated wealth elasticities of ARA, $\xi_{ARA,W}$. The sign of the estimated within-investor elasticity of ARA to wealth (column (2)) is the same as in the cross section: absolute risk aversion is decreasing in investor wealth.

Equation (10) and the estimated wealth elasticity of ARA imply a negative wealth-based RRA to wealth changes for a given investor, $\xi_{RRA,W}$, of −1.85. Column (4) of Table 7 reports the result of estimating specification (12) using the income-based RRA as the dependent variable. The point estimate, −4.35, also implies a negative relationship between this alternative measure of RRA and wealth. These results consistently

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

DV (in log):	(1) ARA	(2) ARA	(3) Income-based RRA	(4) Income-based RRA
	Pooled OLS	Investor FE	Pooled OLS	Investor FE
log(*HouseValue*)	−0.132***	−2.847*	0.158***	−4.351***
	(0.042)	(1.478)	(0.052)	(1.640)
Investor FE	No	Yes	No	Yes
Time trend	Yes	Yes	Yes	Yes
R^2	0.023	0.021	0.027	0.010
Observations	1,843	1,843	1,843	1,843
Investors	1,041	1,041	1,041	1,041

Notes. Estimated investor-specific elasticity of risk aversion to wealth. The left-hand-side variables are the (log) absolute risk aversion (columns (1) and (2)) and income-based relative risk aversion (columns (3) and (4)), obtained for investor i for a portfolio choice in month t. The right-hand-side variables are the (log) median house price in the investor's zip code in time t and an investor fixed effect (omitted). Standard errors are heteroskedasticity robust and clustered at the zip code level.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

suggest that investors' utility function exhibits decreasing relative risk aversion.

The drop in house value is an incomplete measure of the change in investor overall wealth. It is important, then, to analyze the potential estimation bias introduced by this measurement error. Classical measurement error would imply that the point estimate is biased toward 0; this estimate is therefore a lower bound (in absolute value) for the actual wealth elasticity of risk aversion. The (absolute value) of the elasticity could be overestimated if the percentage decline in house values underestimates the change in the investor's total wealth. However, for error in measurement to account for the sign of the elasticity, the overall change in wealth has to be three times larger than the percentage drop in house value.[38] This is unlikely in our setting since stock prices dropped 10% and investments in bonds had a positive yield during our sample period.[39] Therefore, even if measurement error biases the numerical estimate, it is unlikely to affect our conclusions regarding the shape of the utility function. Finally, conditioning on investors that invest more than once in LC may introduce selection bias. If investors with large increments in risk aversion stop investing in LC, our computations would underestimate the effect of wealth shocks on risk aversion. If, on the other hand, investors with large negative wealth stop investing, our results would overestimate the wealth elasticity of risk aversion.

The observed positive relationship between investor RRA and wealth in the cross section from the previous section changes sign once one accounts for investor preference heterogeneity. The comparison of the estimates with and without investor FE in Table 7 confirms it. Moreover, we show in Online Appendix C.1 that the estimated elasticities of risk aversion to wealth, in the cross section of investors and for the same investor, are consistent with the observed relationship between the total investment amount in LC and wealth.[40]

This implies that investors' preferences and wealth are not independently distributed in the cross section. Investors with different wealth levels may have different preferences, for example, because more risk-averse individuals made investment choices that made them wealthier. Alternatively, an unobserved investor characteristic, such as having more educated parents, may cause an investor to be wealthier and to be more risk averse. The results indicate that characterizing empirically the shape of the utility function first requires accounting for such heterogeneity.

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 0.037. We also measure the relative risk aversion based on the income generated by investing in LC (income-based RRA). We find a large degree of heterogeneity, with an average income-based RRA of 2.81 and a median of 1.61. These findings are similar to those obtained in experimental studies in the field and laboratories; they provide an external validation in a real-life investment environment to the estimates obtained from experiments. We show that, since our estimates of risk aversion refer to the local curvature of preferences over changes in income, the parameters estimated here do not depend on a specific utility function and correctly describe agents' preferences in different behavioral models.

We exploit the panel dimension of our data and estimate the elasticity of ARA and RRA with respect to wealth, both in the cross section of investors and, for a given investor, in the time series. In the cross section, wealthier investors exhibit lower ARA and higher RRA when choosing their portfolio of loans within LC. For a given investor, the RRA increases after experiencing a negative wealth shock; that is, the average investor's preference function exhibits decreasing RRA. The contrasting signs of the cross-sectional and investor-specific wealth elasticities indicate that investors' preferences and wealth are not independently distributed in the cross section. Therefore, to empirically characterize the shape of the utility function, one needs to take the properties of the joint distribution of preferences and wealth into account.

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Endnotes

[1] See Kocherlakota (1996) for a discussion of the literature aiming at resolving the equity premium and low risk-free rate puzzles under different preference assumptions. Following the seminal contribution of Campbell and Cochrane (1999), recent work shows that preferences with habit formation produce cyclical variations in risk aversion and decreasing relative risk aversion after a positive wealth shock that can explain these and other empirical asset-pricing regularities (Menzly et al. 2004, Buraschi and Jiltsov 2007, Polkovnichenko

2007, Yogo 2008, Korniotis 2008, Santos and Veronesi 2010). Wealth inequality has also been shown to raise the equity premium if the absolute risk aversion is concave in wealth (Gollier 2001).

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

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

[4] See Calvet et al. (2009) and Calvet and Sodini (2014) for a discussion.

[5] See, among others, Blume and Friend (1975), Cohn et al. (1975), Morin and Suarez (1983), and Blake (1996).

[6] For prior research analyzing investors' behavior in P2P lending, see Iyer et al. (2014), Lin et al. (2013), Marom and Sade (2013), and Ravina (2012).

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

[8] For estimation of risk aversion in real-life environments with idiosyncratic risk, see also Jullien and Salanie (2000), Jullien and Salanie (2008), Bombardini and Trebbi (2012), Harrison et al. (2007b), Chiappori et al. (2008), Post et al. (2008), Chiappori et al. (2009), and Barseghyan et al. (2011).

[9] See, for example, Barsky et al. (1997), Holt and Laury (2002), Choi et al. (2007), and Harrison et al. (2007a).

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

[11] These preference specifications are also consistent with the empirical findings in Calvet et al. (2009). Brunnermeier and Nagel (2008), on the other hand, find support for constant relative risk aversion.

[12] Chiappori and Paiella (2011) find the bias from the cross-sectional estimation to be economically insignificant when risk aversion is measured using the share of risky assets. Tanaka et al. (2010) use rainfall across villages in Vietnam as an instrument for wealth in the cross section and find significant difference between the ordinary least squares (OLS) and instrumental-variable estimators. However, to obtain the elasticity of the agent-specific risk aversion, they must assume that preferences are equal across villages otherwise.

[13] The median investor in our sample period is a retail investor. The composition then shifted toward institutional investors, a common trend in the P2P industry. As of 2014, 80% of investment going into P2P platforms Prosper and Lending Club is from institutional investors (Ford 2014). For the latest figures, refer to https://www.lendingclub.com/info/statistics.action.

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

[15] 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." In addition, 62% of respondents also chose diversification and higher returns as their secondary reason for joining Lending Club.

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

[17] The tool normalizes the idiosyncratic variance into a 1–0 scale. Thus, although the tool provides an intuitive sorting of efficient portfolios in terms of their idiosyncratic risk, investors always need to analyze the recommended portfolios of loans to understand the actual risk level imbedded in the suggestion.

[18] We exploit this variation in Section 5.2 to validate the identification assumptions.

[19] Although LC does not explicitly state on the website that the probabilities of default are idiosyncratic, the optimization tool used to calculate the set of minimum variance portfolios works under this assumption.

[20] The analysis in Section 5.2 confirms that investors' beliefs about the probabilities of default do not differ substantially from those posted on the website, and therefore, σ_z and μ_z are constant across investors.

[21] This framework is equivalent to the one analyzed in Treynor and Black (1973).

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

[23] Since our estimation procedure exploits only buckets with positive investments, we use this margin of choice as an independent test of preference consistency. We show in Online Appendix C.2 that the estimated risk preferences are consistent with those implied by the foregone buckets.

[24] If one of the outside securities in the choice set of the investor is a risk-free asset with return R_f, then $\theta^i \equiv R_f + ARA^i W^i \beta_L^i \text{var}[R_m](\beta_L^i \sum_{z'=1}^{35} x_{z'}^i + \sum_{z'=36}^{Z} \beta_{z'}^i x_{z'}^i)$.

[25] See Treynor and Black (1973) for the original derivation of this result.

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

[27] 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 as proxy for wealth shocks in the empirical analysis.

[28] The variance of the true ARA is calculated as

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

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.

[29] The net worth-based RRA reported here is computed as $RRA_i = \widehat{ARA}_i \cdot NW_i$, where NW_i is the mean point of the net worth interval that Acxiom assigns to each investor in our sample.

[30] This is in line with Barberis and Huang (2001) and Barberis et al. (2006), who 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.

[31] As with the ARA, the estimation variance is small relative to the variance across investments. The standard deviation of $\hat{\theta}$ is 0.028, whereas the standard deviation of θ after subtracting the estimation variance is 0.0271.

[32] See Online Appendix B.1 for the derivation of the efficient portfolios suggested by the optimization tool.

[33] None of the results in this section is statistically significant in the subsample of investors that are renters. This is expected since housing wealth and total wealth are less likely to be correlated for renters, particularly in the time series. However, this is also possibly due

to lack of power, since only a small fraction of the investors in our sample are renters.

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

[35] In this subsample the average zip code house price declines 4% between October 2007 and April 2008. In addition, the time-series house price variation is heterogeneous across investors: the median house price decline is 3.67%.

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

[37] The estimates of ARA and the investment amount are statistically indistinguishable between those that invest once versus those that invest more than once (comparing only the first investment for those that invest more than once).

[38] We estimate the elasticity of ARA with respect to changes in house value to be −2.84. Let W be overall wealth and let H be house value; then, $\xi_{ARA,W} = d\ln ARA/d\ln W = -2.84 \cdot (d\ln H/d\ln W)$. The wealth elasticity of RRA is positive only if $\xi_{ARA,W} > -1$, which requires $d\ln W/d\ln H > 2.84$.

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

[40] Since the ARA and elasticity estimates do not use information on total investment in LC, this consistency test constitutes an independent validation of our conclusions on investors' risk-taking behavior.

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