Insurance and Portfolio Decisions: A Wealth Effect Puzzle

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Abstract

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1 Introduction

The decision to insure against the risk of monetary loss and the decision to invest in risky assets reflect the same, albeit opposite, risk retention tradeoff. Namely, an agent reduces his exposure to risk by purchasing insurance, while he increases his risk exposure by investing. Factors that promote risk taking should therefore lower the demand for insurance and increase the demand for risky assets. Such factors include wealth. Indeed, there is extensive evidence that the wealth elasticity of demand for risky assets is positive.[1] Thus, insurance coverage should decrease with wealth, making insurance an inferior good. The object of this paper is to test the hypothesis that wealth has an opposite effect on portfolio and insurance decisions, and more generally to understand better the link between the two decisions.

To do so, we use survey data for a representative sample of U.S. household heads which combines detailed household level information on wealth composition, portfolio distribution, insurance coverage, and socio-demographic characteristics. The empirical analysis consists of two steps. In step one, we estimate a baseline, easily interpretable, model focussing on auto insurance coverage and investments decisions. Unlike previous literature, the model controls for key covariates such as the value of the good insured, objective and subjective risks and risk attitude. In step two, we conduct a series of robustness checks by considering different specifications and variable definitions, other forms of insurance (homeowner insurance), and, more importantly, a different sample of industry (i.e. not survey) data from a different country (France).

The empirical analysis produces three main results. First, we find strong evidence that insurance is a normal good. That is, all else equal, and in particular after controlling for risks, risk attitude and the value of the good insured, wealthier respondents are found to purchase more insurance coverage. This in itself is a novel and potentially important result that sheds new light on the insurance industry, one of the largest sectors in the world economy.[2] Second, we identify a puzzle, the "insurance-portfolio puzzle", in the sense that, contrary to economic intuition, risky assets holding and insurance coverage both increase with wealth. Third, we find several joint determinants of investment and insurance behavior. In particular, the two decisions respond to subjective expectations and risk attitude in a way consistent with

[1] See e.g. Friend and Blume (1975), Guiso, Tullio and Terlizzese (1996), Perraudin and Sorensen (2000), Carrol (2002), Guiso, Haliassos and Jappelli (2002), Alessie, Hochguertel and van Soest (2004), Campbell (2006), Wachter and Yogo (2010), Calvet and Sodini (2014), or Fagereng Guiso and Pistaferri (2016). Using panel data, Brunnermeier and Nagel (2008), as well as Chiappori and Paiella (2011), find a positive, albeit modest, elasticity of risky asset shares to wealth.

[2] A few empirical analyses provide circumstantial evidence for the hypothesis that insurance may be a normal good (see Millo 2016 for a review). These analyses, however, suffer from limitations, e.g. they rely on aggregate data and do not control for key determinants such as the value of the good insured or the monetary risks faced by the insured (both of which are likely to be correlated with wealth).

theory. We also identify several frictions, including liquidity constraints, financial literacy, or information, that impede both the demand for risky assets and the demand for insurance. Although related to wealth, these frictions are not sufficient to explain the insurance-portfolio puzzle.

To explain this puzzle, we first turn to conventional theory. We show that our results are not consistent with the canonical portfolio and insurance models (Pratt 1964, Mossin 1968, Arrow 1971). We then enrich the model by considering the possibility that insurance and investments decisions are taken jointly, and by adding background risks, wealth dependent losses, limited liability, and liquidity constraints. We conclude that conventional theory is insufficient to explain the puzzle fully. Next, we explore how various behavioral factors may contribute to the puzzle, including prospect theory, context dependent preferences, "peace of mind," or wealth dependent risk perceptions.

This paper contributes to the field of household finance by linking two strands of the literature. First, it relates to the extensive empirical literature on household's portfolio choices (e.g. stock market participation, portfolio diversification, investment mistakes) and their determinants (e.g. risk attitude, wealth, demographics).[3] Second, it relates to the more recent literature that uses micro-level data to explore insurance choices. So far, this literature has focussed mostly on testing for the presence of asymmetric information in various insurance markets,[4] and testing whether risk preferences are stable across contexts.[5] Little is known, however, about the link between households' portfolio and insurance choices. To the best of our knowledge, this paper is the first to identify determinants and frictions that are common to both decisions. More importantly, we identify a puzzle that calls into question standard theory in which portfolio and insurance decisions are modeled as two sides of the coins.

2 Model Specification and Data

2.1 The Baseline Model Specification

Our objective is to investigate the link between wealth and the decisions i) to hold risky assets and ii) to insure against risks. To do so, we follow Einav et al. (2012) and specify a

[3]See Guiso and Haliassos (2002), Campbell (2006), Guiso and Sodini (2013), or Badarinza, Campbell and Ramadorai (2016) for reviews.

[4]See Cohen and Siegelman (2009), Einav, Finkelstein and Levin (2010), or Chiappori and Salanie (2013) for reviews.

[5]See e.g. Barseghyan, Prince and Teitelbaum (2011), or Einav et al. (2012).

joint, seemingly unrelated regression model with limited dependent variables of the form:

$$\begin{cases} I_i = \alpha_0 W_i + \alpha_1 X_i + \alpha_2 Y_i + \varepsilon_i^I \\ R_i = \beta_0 W_i + \beta_1 X_i + \beta_2 Z_i + \varepsilon_i^R \end{cases} \tag{1}$$

where the endogenous variables I_i and R_i, the measures of agent i's insurance coverage and risky assets holding, are left censored (at zero) and possibly right censored depending on the definition of I_i and R_i (see Section 2.2); W_i captures agent i's wealth; X_i is a vector of individual characteristics; Y_i and Z_i are variables pertaining specifically to the agent's insurance and investment decisions, respectively; and $\left(\varepsilon_i^I, \varepsilon_i^R\right)$ is a pair of error terms that follows a bivariate normal distribution with correlation ρ_{IR}. The model is estimated by (full information) maximum likelihood.

The main exercise of the paper is to test the joint hypothesis: $H_0 = \{\alpha_0 < 0, \beta_0 > 0\}$. Thus, we are concerned primarily with identifying the signs of the parameters α_0 and β_0, not their exact values. Although the model in (1) is certainly not immune to possible biases, we will conduct various robustness tests showing that it is adequate to test our hypothesis.

2.2 The data

The baseline model is estimated with data collected in the Survey of Consumer Expectations (SCE) focussing on household's portfolio allocation and auto insurance coverage.

The Survey of Consumer Expectations. The SCE is a monthly, internet-based survey produced by the Federal Reserve Bank of New York since June 2013. It is a 12-month rotating panel (i.e. respondents are asked to take the survey for 12 consecutive months) of roughly 1,300 nationally representative U.S. household heads. The main object of the survey is to collect expectations (both point predictions and density forecasts) for a wide range of economic topics (e.g. inflation, income, spending, household finance, employment, housing). The survey also collects a rich array of socio-demographic variables for each respondent.

The data on wealth composition and portfolio allocation come from two large special surveys on household finance conducted in August 2015 and August 2016 with different set of respondents. In addition, we fielded two special modules on insurance (focussing on car, homeowner, and health insurance), one in September 2015, the other in September 2016. Combining all the data, we have a cross-section of 1,811 respondents: 898 respondents completed the household finance and insurance surveys in August and September 2015, respectively, and 913 respondents completed the two surveys in August and September 2016.

The SCE is quantitative in nature and respondents are used to answer cognitively demanding questions involving dollar amounts, rates and percentages. The household finance survey asks for detailed quantitative information about savings, investments and debts. The insurance survey asks about specific features of the respondent's insurance contracts, including coverage, deductibles, and premiums.[6] To answer as precisely as possible, respondents were encouraged to consult any relevant documentation such as tax returns, bank and investment statements, and insurance contracts.

Measures of auto insurance coverage (I_i). To measure insurance coverage, vehicle owners in the SCE are asked about seven different components of coverage for their main vehicle (defined as the one with the highest current value): 1) Liability coverage (to cover the damage caused by the insured to others), 2) personal injury or medical protection (to pay for the insured and the insured passengers' medical bills resulting from an accident regardless of who is at fault), 3) uninsured and underinsured coverage (to cover the insured expenses when the other party is at fault and does not have any or enough insurance), 4) collision coverage (to repair or replace the insured's vehicle after an accident, regardless of who is at fault), 5) comprehensive coverage (to repair or replace the insured's vehicle after any damage not due to a collision such as theft, hail, fire, vandalism), 6) rental coverage (to pay for a rental car while the insured's vehicle is being repaired), and 7) towing/road side assistance. Based on the responses to these questions we can characterize a respondent's vehicle insurance coverage by a seven-dimensional vector.

The liability and injury components can take three values (ranging from 0 to 2): i) no coverage, ii) the coverage equals the minimum required by law, iii) the coverage exceeds the minimum required by law.[7] The collision and comprehensive components can take five values (ranging from 0 to 4): i) no coverage, ii) coverage with a deductible greater than \$1,000, iii) coverage with a deductible between \$501 and \$1,000, iv) coverage with a deductible between \$251 and \$500, v) coverage with a deductible lower than \$250. The uninsured component can take five values (ranging from 0 to 4): i) no coverage ii) coverage up to \$10k, iii) coverage between \$10k and \$50k, iv) coverage between 50k and \$100k, v) coverage in excess of \$100k. The rental, towing and umbrella components can each take two values (ranging from 0 to 1): i) no coverage, ii) coverage. Observe that each of the seven components of respondent i's insurance coverage vector $C_i = (c_{i,1}, \ldots, c_{i,7})$ is ordered from less to more insurance. In particular, $C_i = 0$ implies that the respondent owns a vehicle but does not have insurance.

[6] The questions asked in the household finance and insurance survey are reported in Appendix 1.

[7] The coverage required by law varies from state to state. Thus, comparing the liability and injury component of respondents in two different states is not perfectly adequate. To address this issue, we conduct a robustness check in which we restrict the sample to states with similar legal minima.

Previous analyses of the U.S. auto insurance market have focussed on a small subset of the coverage vector. For instance, the classic paper of Puelz and Snow (1994) focusses on collision coverage only, while Barseghyan, Prince and Teitelbaum (2011) and Barseghyan et al. (2016) restrict the analysis to the choice of deductibles for collision and comprehensive coverage.[8] Instead, we take a more comprehensive perspective by summarizing the multi-dimensional insurance coverage vector into a single index. Because there is no objective way of doing so, we consider four different indexes. The first index is simply the normalized sum of each component: $I_{i,1} = \sum_{j=1}^{7} c_{i,j}/k_j$, where k_j is the number of possible values the insurance component j can take minus one. For instance, consider a respondent whose insurance contract consists only of the legally required liability coverage. In that case, $c_{i,1} = 1$, $k_1 = 2$ (because the liability coverage component can take three values), $(c_{i,2}, \ldots, c_{i,7}) = 0$, and $I_{i,1} = 0.5$. The index $I_{i,1}$ thus varies from 0 (no coverage) to 7 (full coverage).

The second index is equal to the (empirical) cumulative distribution of the insurance coverage vector: $I_{i,2} = F(C_i)$. Thus, $I_{i,2}$ is a relative index of insurance coverage because it measures how well a respondent is insured compared to the vehicle owners population in the SCE. In particular, $I_{i,2} = 0$ (respectively $I_{i,2} = 1$) means that no other SCE respondent has less (respectively more) car insurance coverage. The third index, $I_{i,3}$, is equal to the first component (i.e. the component that captures most of the variance) in a principal component analysis of the insurance coverage vector. The fourth index, $I_{i,4}$, is a subjective qualitative measure. Namely, respondents were asked to rate their overall level of car insurance coverage on a 7-points Likert scale (from "no coverage at all" to "best coverage possible"). Note that this question was asked only to the respondents in the 2016 survey.

Each of these indexes has advantages and drawbacks. In particular, $I_{i,1}$ is simple to interpret but it gives an equal weight to each insurance component. In contrast, $I_{i,3}$ is less ad hoc but its interpretation is less clear. As shown below, there is a strong correlation between the four indexes. Further, unlike any single component of the vector of insurance coverage C_i, each index is highly correlated with the annual car insurance premium paid by the respondent. Thus, it appears that the four indexes capture relevant and similar information about the respondent's car insurance coverage. The first index, $I_{i,1}$., is used to estimate the baseline model. The other three indexes are used to conduct robustness tests.

Measures of wealth and investments in risky assets (W_i and R_i). Using the data collected in the household finance survey, we calculate the wealth of a household as the

[8]Similarly, Chiappori and Salanié (2000) consider a binary variable of coverage (minimum mandatory coverage versus any type of expanded coverage) to study auto insurance decisions in France, while Cohen and Einav (2007) focus on two deductible levels for the Israeli market.

sum of the current market value of assets owned by every member of the household minus all liabilities owed by household members. Following Brunnermeier and Nagel (2008), we consider two measures of wealth: "liquid" wealth and "financial" wealth (or net worth). The assets considered to calculate a respondent's liquid wealth consist of reported savings and investments (including money on checking and savings accounts, certificates of deposit, stocks, bonds, mutual funds, Treasury bonds), retirement savings (including money saved in an IRA, 401K, 403(b), 457, or thrift savings plan), as well other miscellaneous (non housing) reported savings and assets, including jewelry, valuable collection(s), vehicles, cash value in a life insurance policy or rights in a trust or estate. The liabilities considered to calculate a respondent's liquid wealth consist of any reported outstanding (non-housing) debt, including balances on credit cards, car loans, student loans, personal loans, and medical or legal bills.

The assets considered to calculate a respondent's financial wealth consist of the liquid assets just listed plus the reported current value of the household's primary home (i.e. how much the respondent thinks it would sell for on today's market), the value of other home(s) owned by the household, as well as the value of shares owned in any business. The liabilities considered to calculate a respondent's financial wealth consist of the liquid liabilities listed above plus the reported total amount of outstanding loans against the household's home(s), including all mortgages and home equity loans.

We consider two measures of risky assets. The risky liquid assets consist of the stocks and mutual funds owned by the respondents, while the risky financial assets also include housing and business assets. Further, the two measures of risky investments are considered both in absolute terms (i.e. as a dollar amount) and in relative terms (i.e. as a share of the corresponding liquid or financial wealth measure). The baseline model is estimated using liquid wealth and the share of risky liquid assets. Robustness tests are conducted using the other measures of wealth and risky investments.

Insurance and investments specific covariates (Y_i and Z_i). The variables relevant specifically to a respondent's insurance decision consist of the value of the respondent's main vehicle (i.e. how much the respondent thinks it would sell for on today's market), the annual premium paid by the respondent to insure this main vehicle,[9] the population density in the respondent's zip code (a variable typically considered a proxy for risks), a measure of the respondent's objective risks (based on the reported sum of all monetary damages incurred over the past two years, including those for which no insurance claim was submitted), a measure of the respondent's subjective risks (based on the reported sum of all monetary

[9]Note that the premium is not the price of insurance, it is the total expense on insurance.

damages the respondent expect to incur over the next two years),[10] as well as a qualitative measure of the respondent knowledge of his car insurance contract.[11]

The variables relevant specifically to portfolio decisions include a measure of expected returns (the respondent expected change in the U.S. stock market over the next 12 months) and a qualitative measure of the respondent knowledge about his debts and savings.

Individual characteristics (X_i). We control for standard socio-demographic variables such as the respondent's age, gender, race, educational attainment, marital and employment status, and family composition (i.e. whether or not the household includes children). In addition, we take advantage of the rich array of household level information collected in the SCE to control for behavioral factors such as a measures of the respondent's financial literacy (adapted from Lusardi 2007),[12] liquidity constraints (the reported probability to come up with $2,000 if the need arose), credit worthiness (the respondent's reported credit score), and subjective risk tolerance (based on Dohmen et al. 2011).[13]

3 Descriptive Statistics and Prima-Facie Evidence

Descriptive statistics are reported in Tables 1 to 7 and Figures 1 to 4. Overall, it appears that the sample is reasonably representative of U.S. household heads and the data collected on wealth composition, portfolio allocation and insurance coverage are sensible.

As shown in Table 1, slightly less than half of the respondents (the household head or co-head) is a female. Two out of three respondents are married or living with a partner

[10] The respondents are asked to "consider all the damages you may incur on that vehicle which you (or your insurance) would be financially responsible for (that is, bodily and property damages to you and to others due to collision(s) you caused, theft(s), hail, vandalism, and such)". The variable "Objective Risk Auto" takes the value 0, 1 or 2 when the response is $0, between $0 and $1,500, and greater than $1,500, respectively. We also ask a similar question about the damages expected over the next two years. To make the measures of risks comparable, the variable "Subjective Risk Auto" is set to 0, 1 or 2 when the response is less than $250, between $250 and $1500, and greater than $1,500, respectively.

[11] An issue researchers have faced is that damages are typically only observed if they lead to the submission of an insurance claim. This is potentially a problem since the probability to submit a claim likely depends on the coverage (e.g. drivers with higher deductibles should submit fewer claims). We do not face this problem here since our measures of risks include all damages including those for which the respondent does not submit a claim.

[12] Here is an illustration of the type of questions we asked to elicit financial literacy: "If you have $100 in a savings account, the interest rate is 10% per year and you never withdraw money or interest payments, how much will you have in the account after: one year? two years?".

[13] Respondents are asked to assess their willingness to take risk regarding financial matters using a Likert scale ranging from 1 (Not willing at all) to 7 (very willing). This instrument has been shown to produce meaningful measures of risk preferences. In particular, Dohmen et al. (2011) find that the risk tolerance reported on this scale is consistent with the risk preference elicited with a financially incentivized lottery-type experiment (Holt and Laury 2002) and correlates with actual (i.e. non-experimental) financial behavior.

and 39% of households have children currently living in the primary home. The median respondent in the survey is 49 and has a Bachelor degree. Table 1 also indicates that the sample composition remained stable with respect to demographics between the 2015 and 2016 surveys. Further, as documented in Armantier et al. (2017), SCE respondents are essentially representative of the U.S. population of household heads with respect to gender, race, family composition, and geography. SCE respondents, however, tend to be slightly older and slightly more educated than in the 2010 census.[14]

We report in Figure 1 the cumulative distributions of liquid and financial wealth, as well as the cumulative distributions of the corresponding shares of risky assets. Consistent with (e.g.) Saez and Zucman (2016), the distribution of (liquid and financial) wealth has a strong positive skew with a long right tail. Note also in Figure 1 that 17% (13%) of the respondents report having negative liquid (financial) wealth, meaning that their total debt exceeds the current market value of their assets.[15] As indicated in Table 2, the mean and median liquid wealth reported by SCE respondents are \$280K and \$83k respectively, with a slight increase (5%) between 2015 and 2016. Over half of liquid assets consist of retirement savings, while a quarter consists of money in checking and saving accounts. As seen in Figure 1, roughly half of the respondents (51.1%) report owning stocks (i.e. risky liquid assets) directly or indirectly in pooled investment funds. Conditional on owning stock, the average share of risky liquid assets is roughly one third (see Table 2).

Financial wealth (i.e. liquid wealth plus housing and business equity), with a mean of \$427K and a median \$135k, is 60% larger than liquid wealth (see Table 3). This is explained by the large share of assets invested in housing. Indeed, the homeownership rate is 68% in our sample, and the average (median) home equity (conditional on owning a home) is \$199k (\$122k). The conditional share of risky financial assets is 62%, but 21% of our respondents report owning no risky assets (see Figure 1 and Table 3). These statistics about wealth composition align well with similar data from the Census Bureau, the Survey of Consumer Finance, and previous literature (e.g. Brunnermeier and Nagel 2008).[16]

We report in Table 4 descriptive statistics pertaining to auto insurance coverage. Nearly all of the respondents (97%) report owning a vehicle (i.e. a car, light truck or SUV) which they evaluate at \$15k on average.[17] The proportion of respondents who report having in-

[14]we refer the reader to Armantier et al. (2017) for a discussion of the SCE technical features, such sample frame, implementation, response rate, representativeness, and panel stability.

[15]As discussed in Armantier et al. (2016), this result, which is also found Survey of Consumer Finance, is consistent with a standard life cycle model in which households take on debt when young.

[16]Unlike Brunnermeier and Nagel (2008), we do not exclude households with liquid or net wealth below \$10k. Doing so would substantially reduce our sample (by roughly 20%). Further, excluding the poorest households does not seem appropriate for our analysis.

[17]These figures are in line with is the University of Michigan's *Transportation Research Institute* as well

curred some damages over the past two years is 32%. The sum of all vehicle damages actually incurred over the past 2 years ($1.5k on average) and expected to incur over the next 2 years ($1.9k on average) are consistent (see Table 4). The correlation between the variables "Objective auto risk" and "Subjective auto risk", however, is only 0.3. This therefore suggests that the two measures of risks capture different information. Only 1% of vehicle owners report not being insured.[18] The premiums SCE respondents report paying for their car insurance appear sensible. In particular, the average and median annual premiums in Table 4 ($994 and $900, respectively) are in line with the 2015 figures the *National Association of Insurance Commissioners* (*NAIC*), $1009 and $938, respectively.

We report in Figure 2 the distribution of coverage for each component of the auto insurance vector. Roughly 60% of respondents report having liability and personal injury coverage in excess of the legal requirement. The proportion of respondents with collision and comprehensive coverage is 82% and 79%, in line with the 2015 *NAIC* estimates of 78% and 73%, respectively. The most common range of deductibles for collision and comprehensive coverage is between $251 and $500, consistent with Barseghyan et al. (2011, 2016). While the vast majority (80%) of respondents report having uninsured insurance, coverage seems to be somewhat limited for most (2/3 of the sample has less than $50k in coverage). Finally, slightly more than half of the respondents have rental and towing coverage.

Table 5 and Figure 3 shows that the four indexes of insurance coverage are highly correlated and have relatively similar distributions. Further, we can see in Table 6 that the correlation between the index of coverage $I_{i,1}$ and the insurance premium driver i paid is 0.23. Thus, the simple index appears to be informative about insurance coverage. In contrast, the highest correlation between the premium and any of the seven components of car insurance coverage is 0.11 in Table 6 (for rental coverage). This therefore provides evidence that the simple index $I_{i,1}$ captures car insurance coverage better than any single component.[19]

We conclude this section by providing prima-facie evidence of the link between wealth, auto insurance coverage and risky investments. In Figure 3, we plot the average share of risky liquid assets (X-axis) and the average index of insurance coverage I_1 (Y-axis) for each decile of the liquid wealth distribution. For instance, we can see that respondents in the highest (10th) decile of wealth invest on average 41% of their liquid wealth in risky assets, while their average index of car insurance coverage I_1 is 5.5 out of 7. Figure 4 reveals a nearly

as estimates from *Edmunds*.

[18]This figure is substantially lower than the *Insurance Information Institute* estimate that 13% of American drivers had no vehicle insurance in 2012.

[19]Regressions accounting for relevant determinants such as objective and subjective risks, car value, or the driver's age also indicate that our simple index of insurance coverage dominates any single component of coverage to explain the premium paid.

perfectly monotonic relationship: as wealth increases both auto insurance coverage and the share of liquid wealth households invest in risky assets increase. This therefore provides prima-facie evidence against the hypothesis that more affluent households simultaneously invest more aggressively and insure more conservatively. In the next section, we test more formally this hypothesis by estimating the baseline econometric model in (1) and controlling for relevant explanatory variables.

4 Estimation Results from the Baseline Model

We report in Table 8 the estimation results for the baseline regression model. Recall that the baseline model is specified in equation (1) with the dependent variables being the simple index of auto insurance coverage I_1 and the share of risky liquid assets, while the variable of interest is liquid wealth. We consider six different specifications.

Model 1: The direct effect of wealth. The first specification (Model 1 in Table 8) controls only for wealth. We find the wealth parameters to be positive and highly significant in each of the insurance coverage and risky investments equations. The null hypothesis $H_0 = \{\alpha_0 < 0, \beta_0 > 0\}$ in equation (1) is therefore unambiguously rejected (*P-value*=6.7E-5). Thus, investments in risky assets and car insurance coverage are both positively correlated with wealth. The first result is consistent with previous literature showing a positive elasticity of risky asset holdings to wealth (see the references in footnote 1). The second result is new to the literature, to the best of our knowledge. In particular, it suggests that insurance is a normal good, in contrast with the seminal paper of Mossin (1968). The combination of the two results, i.e. rejecting $H_0 = \{\alpha_0 < 0, \beta_0 > 0\}$, also suggest that the decision to insure and the decision to invest in risky assets may not be characterized as an opposite risk retention tradeoff. As we shall see below, this finding appears to be robust as it is confirmed in all the regressions and robustness checks we performed.[20]

To conclude with Model 1, note that ρ_{IR}, the correlation between the error terms ε_i^I and ε_i^R in equation (1), is positive and significant. As we shall see, this result is robust as well. While the magnitude of the correlation, around 0.1, is consistent with Einav et al. (2012), the sign is not. Einav et al. (2012) find a negative correlation between the errors terms in their risky investments and insurance coverage econometric equations, while we consistently find a positive correlation. We conjecture that this result may be due to data differences between the two studies. In particular, Einav et al. (2012) focus on 401(k) asset allocations

[20]Recall that our focus is primarily on the sign of the wealth parameters. Nevertheless, we will gauge the economic implication of the parameters' magnitude later in section 6.

and employer provided insurance in the health domain. Finally, finding that ρ_{IR} is significant provides support for our econometric approach in which the decisions to insure and invest are modeled jointly.

Models 2 and 3: Characteristics of insurance contracts. We augment the specification in Models 2 and 3 of Table 8 by controlling for factors that should enter a typical auto insurance contract. Starting with Model 3, we find that, as expected, the level of insurance coverage increases with the value of the good insured and the actual risks faced by the driver. In contrast, we find a positive but insignificant effect of the population density, a variable practitioners often believe to complement past damages as a proxy for risks. Finally, observe that while the relation between insurance coverage and premium is positive and highly significant in Model 2 (consistent with intuition), the effect essentially vanishes in Model 3. In other words, it appears that most of the coverage-premium relationship is captured by other characteristics of the insurance contract.[21]

Model 4: Standard socio-demographic characteristics. In Model 4 of Table 8 we add controls for standard socio-demographic characteristics. Observe first that the fit of the model improves substantially (as indicated by the lower *AIC* criterion). Further, the wealth parameters, while lower, remain positive and highly significant in both the insurance and risky investment equations. The estimates from Model 4 also indicates that portfolio and insurance decisions vary with socio-demographic characteristics. In particular, we find that older households have significantly more car insurance coverage and a safer portfolio.[22] Education also plays a prominent role. Respondents with more (respectively less) than a Bachelor degree purchase more (respectively less) insurance coverage and invest a higher (respectively lower) share of their liquid wealth in risky assets.[23]

Gender, marital status and credit worthiness appear to influence only portfolio decisions. Namely, households with a female respondent tend to invest less in risky assets, while the portfolio of couples (i.e. those married or leaving with a partners) and households with higher credit scores are more heavily skewed toward risky assets. As we shall see, the first result (about gender) does not seem to be robust as it ceases to hold when we add more

[21]This result is consistent with a standard insurance pricing model in which the information contained in the premium reflects in equilibrium the characteristics of the insurance contract, i.e. *P*=f(coverage, risks, ...)*.

[22]The second result is consistent with (e.g.) Fagereng, Gottlieg and Guiso (2017) who find that, as households age, they tend to rebalance their portfolio away from stocks. Note also that adding a quadratic term in age in the econometric model, reveals a significant hump shape in the risky investment equation (not in the insurance equation), but it does not improve the fit of the model substantially.

[23]The positive effect of education on risky portfolio allocation is consistent with (e.g.) Campbell (2006), or Guiso, Haliassos and Jiappelli (2002).

controls. Finally, we fail to identify a significant effect of employment status, race, and family composition (i.e. whether or not the household include children).[24]

Model 5: Behavioral factors. We augment the specification in Model 5 of Table 8 by adding controls for subjective risks, financial literacy, information and liquidity constraints. These behavioral factors all seem to have strong explanatory power. In particular, we find clear evidence that expectations matter. Indeed, the parameters associated with the two subjective measures of auto and investment risks are positive and highly significant. Thus, respondents who have higher expectations about the stock market invest more aggressively (consistent with Arrondely, Calvo-Pardoz and Tasx 2014), while respondents who expect to incur more auto related damages purchase more insurance coverage. It is interesting to note that the measure of objective auto risks is positive and significant in Models 3 and 4, but it becomes insignificant in Model 5 when we control for subjective risks. Thus, consistent with intuition, we find that a respondent's decision about the amount of auto insurance to purchase is driven more by his subjective risks perception, than the objective risks he faces.[25]

Information, or what Guiso and Jappelli (2005) call *awareness*, also plays a significant role. Respondents who report having better knowledge of their own debts and savings invest more in risky assets, while respondents who report better knowledge of their car insurance policy have more coverage. Similarly, Guiso and Jappelli (2005) and Gargano and Rossi (2017) find that information and attention are positively related to risky portfolio allocation and investment performance.

Respondents who report being more liquidity constrained (i.e. with a lower probability to come up with $2,000 if the need arose) have less insurance coverage and fewer risky assets. Thus, we find evidence supporting the common beliefs among practitioners that the lack of sufficient insurance coverage may be driven in part by binding budget constraints (Kunreuther and Pauly 2006, Brobeck and Hunter 2012).[26] This market friction, however, is not sufficient to explain the insurance-portfolio puzzle. Indeed, note that the wealth parameters, although slightly lower in Model 5 compared to Model 4, remain highly significant in both equations. Thus, wealth and liquidity constraints appear to play a significant but separate role on insurance and portfolio decisions.[27]

[24] To avoid possible multicollinearity issues between wealth and income, we did not control for the household's income in the baseline model.

[25] This does not imply that respondents have biased beliefs or do not act rationally. It may be that agents have additional information in which case the subjective risk measure may be a better proxy for the risks the respondent actually faces than our objective risk measure based on the past damages.

[26] See also "Study on the Affordability of Personal Automobile Insurance" U.S. Dept of the Treasury (2017).

[27] The correlation between wealth and the measure of financial liquidity (0.22) is positive but not perfect in

Finally, our results suggest that all else equal, and in particular after controlling for educational attainment, respondents with lower financial literacy purchase less insurance and possess a less risky portfolio of assets. Similarly, Fang, Keane and Silverman (2008) find that elderly people with higher cognitive abilities are more likely to purchase Medigap insurance (a health insurance sold to fill "gaps" in coverage of the basic Medicare plan), while van Rooij, Lusardi and Alessie (2011) and Lusardi, Michaud and Mitchell, (2012) find low financial literacy to be a major impediment to stock market participation.

This set of results, identifying common market frictions for portfolio and insurance decisions, are original and may have policy implications. In particular, although we make no claims about causality, it is conceivable that a regulator may be able to provide financial education, information, or ease liquidity constraints to manage insurance and investment behaviors. In particular, Bhargava, Loewenstein and Sydnor (2015) conducted an experiment showing that improving insurance literacy lead to better coverage choices.

Model 6: Risk attitude. We conclude by adding a measure of the respondent's risk attitude in Model 6 of Table 8. Before we discuss the estimation results, we make two briefs comments. First, in theory wealth affects investment and insurance decisions only through the Arrow–Pratt coefficient of absolute risk aversion $A(.)$. Thus, if our measure of risk attitude is a sufficient statistic for $A(.)$, then the wealth parameters should become insignificant in Model 6. Second, we document in Figure 5 the link between a respondent's wealth and our subjective measure of risk tolerance, the reported willingness to take risk about financial matters (ordered from 1, not willing at all, to 7, very willing). To make the chart clearer, we plot the average measure of risk tolerance for each decile of wealth. The chart exhibits a monotonic relationship consistent with DARA. This finding is consistent with numerous empirical and experimental analyses (add cites) and it provides support for the standard portfolio and insurance models which assume DARA (e.g. Pratt 1964, Mossin 1968).

Now, turning to the estimation results in the last column of Table 8, we can see that our measure of risk attitude has a sensible and highly significant effect: respondents who report being more willing to take risks regarding financial matters have less insurance coverage and riskier portfolios.[28] Note also that the significance and the magnitude of the other parameters vary little compared to Model 5. In particular, contrary to our prediction, the wealth parameters remain positive and highly significant in both the investment and insurance equa-

our data. This reflects the well documented fact that some households although wealthy are cash strapped (see Lusardi, Schneider and Tufano 2011, or Lusardi, Mitchell, and Oggero 2017).

[28]This result is consistent with Dohmen et al. (2011) who also find this measure of risky tolerance to have significant explanatory power for real life financial decisions.

tions. This result may imply that our measure of risk attitude, although informative, does not capture properly $A(.)$, the coefficient of absolute risk aversion. Alternatively, our result may suggest that wealth affects insurance and investment behavior outside the utility function channel, a possibility we explore in section 7. More generally, our results suggest that the effect of wealth on insurance and investment decisions is not purely as a risk preference shifter. Indeed, we find that wealthier respondents are more risk seeking (Figure 5), but nevertheless they tend purchase more insurance coverage.

5 Robustness Checks

We conduct in this section a series of checks to test the robustness of the results obtained with the baseline specification in Model 6 of Table 8.

Alternative indexes of insurance coverage. We start by considering alternative definitions for auto insurance coverage. The dependent variable for the insurance equation in Models 1, 2 and 3 of Table 9 are $I_{i,2}$ (the relative index based on the empirical cumulative distribution of coverage), $I_{i,3}$ (the first component in the principal component analysis of coverage) and $I_{i,4}$ (the subjective measure in the 2016 survey), respectively.

A potential issue with the insurance indexes considered so far is that the legal requirements for auto insurance differ from states to states. Thus, comparing insurance choices across respondents from different states may not be appropriate. To address this issue, we estimate the baseline model after restricting the sample to respondents from state with similar legal requirements. These requirements are summarized in the form *"$X/Y/Z$"* where X, Y and Z are in thousands of dollars and represent the minimum coverage required for bodily injury per person, bodily injury per accident and property damage per accident, respectively.[29] In 2016, the legal requirements varied from 10/20/10 in Florida to 50/100/25 in Maine and Alaska. In Table 9, we restrict the sample to states with legal minima between 20/40/10 and 20/50/25 in Model 4, and between 25/50/10 and 25/50/25 in Model 5. Doing so reduces the sample size by 43% for Model 4 and by 56% for Model 5.

In principle, liability losses are only bounded by the driver's wealth. As discussed in more details in section 7, the presence of such wealth dependent losses could explain why more affluent drivers prefer to purchase more insurance coverage. To evaluate the extent to which our results are driven by this effect, we redefine the simple index of coverage absent any liability component. In Model 6 of Table 9, the new index $I^{-}_{i,1}$ is now a combination of only the collision, comprehensive, rental and towing components.

[29]Some states also have secondary requirements for (e.g.) medical payments or personal injury.

As can be observed in Table 9, virtually all the results discussed in the previous section still hold under these alternative specifications. Most importantly, the wealth parameters, remain positive and highly significant for all specifications, even in Model 6 where the index of insurance excludes liability coverage.

Alternative measures of wealth and investment in risky assets. The baseline model was estimated using a respondent's liquid wealth and the share of risky liquid assets. In Table 10, we test the robustness of our results to alternative definitions of wealth and risky assets. In Model 1, wealth is defined as financial wealth (i.e. liquid wealth plus housing and business equity) and the risky investment measure is the share of risky financial assets. In Model 2, wealth is defined as liquid wealth (as in the baseline model), but the risky investment measure is the dollar amount invested in risky liquid assets. Finally, Model 3 has the financial wealth and the amount invested in risky financial assets. Again, we can see in Table 10 that, with a few minor exceptions, the results obtained with these alternative definitions remain consistent with the baseline specification.

2015 and 2016 Data. In Table 11, we re-estimate the baseline model after restricting the sample to the data collected in either the 2015 survey (column 2) or the 2016 survey (column 3). We also include the estimates from the baseline model in the first column for reference. Although the magnitude, and in some cases in the significance of the estimated parameters differ slightly compared to the baseline model (as may be expected due to the smaller sample sizes), the nature of the results, and in particular the effect of wealth, remain virtually unchanged.

Nonlinear wealth effects. Wealth enters the baseline model's specification linearly in equation (1). One may wonder, however, whether the insurance-portfolio puzzle we identified is driven predominantly by respondents on the upper or on the lower tail of the wealth distribution. To test this hypothesis, we modify the baseline model by considering various nonlinear wealth effects in Table 12. Model 1 accounts for the log of wealth,[30] Model 2 has a cubic polynomial in wealth, while Model 3 includes dummies for each quintile of wealth with the reference group being the central quintile (i.e. respondents located within 10% of median of wealth). Four points are worth noting in Table 12. First, in each regression most (when not all) of the wealth parameters are significant, and they confirm the insurance-portfolio puzzle, i.e. the positive effect of wealth on insurance coverage and risky investments.

[30]Because some respondents have negative wealth, the variable is defined as $Ln(Wealth_i + MinWealth + 1)$ (where $MinWealth$ is the lowest liquid wealth in the sample), so as not to exclude any respondent.

Second, the sign and the magnitude of the other parameters remain virtually unchanged. Third, the fit of the model only improves modestly when accounting for non-linear wealth effects (as indicated by the *AIC* criteria at the bottom of Table 12). Fourth, as can be seen in Figure 6 where the marginal effects of wealth in each model is plotted, the effect of wealth on insurance coverage and risky investments appears to be qualitatively consistent across models. In particular, note in Model 3 of Table 12 that the parameters associated with the wealth quintile dummies increase monotonically. Thus, we find no evidence that the insurance-portfolio puzzle is driven by a specific segment of the wealth population. Instead, the effect of wealth appears nearly linear and seem to apply fairly equally to anyone regardless of their position on the wealth distribution.

Wealth endogeneity: IV models. We now account for the possibility that wealth may be endogenous. In Table 13 the effect of wealth is identified using two instruments that are relatively standard in the literature. The first measures unanticipated changes in wealth (as proposed by Guiso and Paiella 2001) and the second local house price variations over time (as in Hurst and Lusardi 2004). More specifically, Model 1 reports on the estimation of the baseline model in which wealth has been instrumented by the median house price growth over the past 3 years within the respondent's zip code. In Model 2 wealth is instrumented by reported unexpected changes in the respondent's wealth over the past 12 months. Finally, the two instruments are combined in Model 3. Observe first in the last row of Table 13 that the F-statistic in the first stage regressions are relatively large, and certainly larger than the rule of thumb of 10 suggested by Staiger and Stock (1997). Thus, our instruments have explanatory power and we find no evidence of a weak instruments issue. Next, note that the effect of wealth remains positive and highly significant in every regression. Thus, the insurance-portfolio puzzle is confirmed even when accounting for the possible endogeneity of wealth.[31]

Interaction effects. It may be argued that wealth affects the value of the good insured (e.g. wealthier agents purchase more expensive cars) or that the wealthy do not face the same monetary risks (e.g. expensive cars may be more likely to be stolen). Thus, there may be an indirect effect of wealth through the car value or the risks faced. If so, then the baseline model we estimated may not have captured properly the true effect of wealth on insurance coverage. To account for this potential indirect channel and to identify better the pure effect

[31]We considered additional instruments including a measure of the respondent's income growth (as in Brunnermeier and Nagel 2008), recent changes in credit score, expected housing equity gains, or expected change in credit availability. While these instruments did not perform as well in the first stage, the nature of the results in the second stage did not change in a meaningful way.

of wealth, we add in Table 14 interaction effects in the insurance coverage equation. The results reported in Table 14 indicate that none of the interaction effects are significantly different from zero. Further, the nature of the results obtained with the baseline model remains unchanged. Thus, we find no evidence of an indirect effect of wealth on insurance coverage and investment in risky assets.

Home insurance. We now test whether the insurance-portfolio puzzle is confined to auto insurance or whether it applies more broadly to other forms of insurance. To test this hypothesis, we now focus on the information collected in the SCE about homeowner and renter insurance. To measure coverage, respondents are asked about nine different components of coverage for their primary home : the amount of coverage on 1) the dwelling (the home itself), 2) personal property and 3) liability; 4) the deductible; and whether the respondents contracted additional 5) flood, 6) earth movement (earthquake, mudslides or landslides), 7) windstorm, 8) floater or rider (to cover special items such as expensive jewelry or antiques), or 9) umbrella (to cover lawsuits and claims) insurance. Based on the responses to these questions we constructed a simple index of coverage similar to $I_{i,1}$. In addition, SCE respondents are asked to report the replacement cost (the cost of rebuilding the home and replace personal property), the premium paid, objective and subjective measures of risks (the value of the damages incurred over the past 2 years and expected to occur over the next 2 years), and knowledge of their home insurance contract.

Summary statistics for homeowner insurance are provided in Table 7. Similar to auto insurance, the data collected for home insurance appear sensible. Out of the 1,229 homeowners in the sample, 98% report having homeowner insurance, in line with the 2015 estimate of 95% by the *Insurance Information Institute* (*III*). The average premium reported is $1,152, similar to the 2015 *III* figures of $1,110. The most frequent range of deductible in the data is “$251 to $1,000” with a share of 62% (consistent with Snydor 2010). The proportion of homeowners who report having coverage between $50k and $300k is 64%, compared to 72% in 2015 according to the *NAIC*.[32] The proportion of homeowners who report having additional insurance is 12% for flood insurance (the 2015 *III* estimate is 14%), 8% for earth movement insurance (the 2015 *III* estimate is 10%), 11% for windstorm insurance, 12% for floater insurance, and 20% for umbrella insurance (compared to 10% according to a 2013 Consumer Reports study).[33]

[32]For the 577 renters in the sample, 58% report having renter insurance, the average premium is $266 and 84% report having coverage below $75k, compared to the 2015 *III* estimates of 40%, $190 and 88%, respectively.

[33]The decision to subscribe additional coverage generally seems to make sense. In particular, respondents with earthquake and windstorm insurance are predominantly located in the west and south respectively,

We report in Table 15 the estimates of the baseline model with home insurance. The first column includes homeowners only, while the second column includes homeowners and renters. Qualitatively the results are remarkably similar for auto and home insurance. In particular, the two insurance decisions share most of the same determinants. Further, the wealth parameters are positive and significant in all equations in Table 15 and the null hypothesis $H_0 = \{\alpha_0 < 0, \beta_0 > 0\}$ is again unambiguously rejected (*P-value*=3.6E-4). Thus, the insurance-portfolio puzzle is found equally with auto and home insurance.

Administrative data from France ________________

6 Magnitude of the Insurance-Portfolio Puzzle

Here are some questions it would be nice to address if we want a top publication, but I do not know how to address them....

- How big is the puzzle?
  - Our econometric estimates suggest that moving from the first quartile of liquid wealth ($10k) to the 3rd quartile of liquid wealth ($350k) increases the share of liquid risky assets from 9% to 22% (an increase of 0.57 standard deviation or 11 percentile points), and it increases the index of auto insurance coverage from 3.9 to 4.8 (an increase of 0.51 standard deviation or 17 percentile points).
  - Our econometric estimates suggest that moving from the 10th percentile of liquid wealth (-$18k) to the 90th percentile of liquid wealth ($800k) increases the share of liquid risky assets from 4% to 43%, (an increase of 1.7 standard deviation or 33 percentile points), and it increases the index of auto insurance coverage from 3.6 to 5.5 (an increase of 1.15 standard deviation or 42 percentile points).
  - Is this big?
- How costly is the puzzle?
  - Are the costs stemming from the puzzle modest, and therefore explicable by relatively small frictions ignored in standard theory, or are they large and accordingly hard to rationalize?
  - Calvet Campbell and Sodini AER 2009 find that richer, better educated households tend to make fewer investment mistakes, i.e. they are better diversified,

while respondents with umbrella insurance tend to have higher wealth.

display less portfolio inertia and they are less exposed to the disposition effect (i.e. they have a weaker tendency to hold losing and sell winning stocks). However they find (JPE 2007) that the economic cost of low diversification and non-participation are in fact modest.

  – How should we evaluate the cost of the puzzle? What are the benchmark for appropriate portfolio and insurance choices?

- Who is making a mistake?
  – Are the rich too insured and their portfolio too risky or are the poor not sufficiently insured and their portfolio risk allocation too conservative?
  – There is a portfolio literature showing that the poor are more prone to investment mistakes (e.g. Campbell 2006, Gaudecker JF 2015). This would suggest that the poor do not have enough insurance.
  – However, there is a literature showing excessive demand for low deductibles, and extended warranties which suggest that people fail to self-insure in the way the standard model would predict. Data collected in the SCE seems to support the hypothesis that this tendency is correlated with wealth (i..e wealthier respondent reported being more likely to purchase extra insurance on electronics).
  – Can we make a back of the envelope calculation about what insurance coverage and/or the risky share should be for a "poor" (e.g. at the 10 percentile of wealth) and a "rich" (e.g. at the 90 percentile of wealth). For the two agents we know their wealth, distribution of risks and we have a measure of their risk attitude. Could we make an assumption about their utility function? Then can we compare the predicted coverage/portfolio to the actual coverage/portfolio to see if one group make a major mistake? Einav et al. 2012 (section 4.2 and appendix) conduct such an exercise.

7 Possible Explanations for the Puzzle

7.1 Standard theory

A number of explanations using standard theory can be advanced to explain the puzzle that insurance is a normal good.

DARA versus IARA. Standard theory predicts that insurance decreases with wealth iff DARA (Mossin 1968); see Appendix A.1. This means that insurance is a normal good if risk preferences display instead increasing absolute risk aversion (IARA). Therefore, IARA can explain the puzzle.Yet, IARA does not seem empirically plausible. Experimental (Binswanger 1981, Levy 1994), survey (Barsky et al. 1997, Sahm 2007, Guiso and Paiella 2008) as well as field data (Chavas and Holt 1996, Guiso et al. 1996, Brunnermaier and Nagel 2008) usually give support to DARA. Second, it is not clear how to explain why in our analysis insurance is a normal good consistent with IARA, while in the same time investments in risky assets increase in wealth consistent with DARA.

Multiple decisions. A handful of papers (Dionne and Eeckhoudt, 1984; Eeckhoudt et al., 1997; Meyer and Meyer, 2005; Loubergé and Watt, 2007) show, using a model involving multiple decisions, that insurance demand may increase with wealth, even under DARA. An intuition for this result is provided by the notion of "background risk". Suppose that an agent makes two decisions, an insurance and a portfolio decision. Suppose then that a wealthier agent invests more in risky assets because of DARA. This agent thus faces a background risk which may induce him to behave in a more risk averse manner and in turn purchase more, and not less, insurance. This argument is however not very convincing for a couple of reasons. First, the argument is local, in the sense that the papers cited above only show that the effect is ambiguous in the sense that insurance may be "locally" a normal good. Hence, these models could not explain the systematic positive effect of wealth on insurance demand. Second, we study specifically in appendix A.2 a model where insurance and portfolio decisions are made simultaneously. We first show that the presence of portfolio investment opportunities indeed increase insurance demand, and thus act as a background risk. Nevertheless, we show that insurance demand still decreases everywhere with wealth and that the investment in risky assets still increases everywhere with wealth iff DARA. Hence, the standard results regarding the effect of wealth on the insurance and portfolio decisions is fully preserved despite the fact that the two decisions are considered simultaneously and not separately. Furthermore, we show in Appendix A.3 that the result is also preserved when a savings decision is made simultaneously with another insurance decision, as in Aura et al. (2002).

Wealth-dependent loss It is natural to assume that the insured good (car, house) has a higher value when the agent is wealthier. Since insurance is expected to increase with the value of the insured good, this effect counteracts the negative effect of DARA on insurance demand. Indeed, we show a case in Appendix A.4 that insurance is a normal good even under DARA as soon as the elasticity of the good with respect to wealth is high enough. This effect may explain some previous empirical results that insurance has been found to be a normal good (Guiso and Jappelli 1998). Nevertheless, it can hardly explain our results as we systematically control for the value of the insured good in our empirical analysis.

Liability insurance Consider the following reasoning. Suppose that an agent purchases liability insurance, in the sense that he insures against the risk of losing all his wealth. In that case, the insured good depends on wealth. Consistent with what we said in the previous paragraph and what we show in Appendix A.4, the theoretical result that wealth decreases insurance demand iff DARA does not hold anymore in that case. In other words, a wealthier agent has an incentive to purchase more insurance because he faces a greater loss. This effect is difficult to control in our US data because the insurance contract for the insured good (car, house) combines coverage for the loss of that good (e.g., collision insurance) together with liability insurance. Yet, the price of insurance is global, and thus the separate effects of each insurance coverage cannot be distinguished. Nevertheless, our french data provide some control for this. Indeed, in France, liability insurance is compulsory for everyone. Therefore, the variation in coverage and in price only concern aspects that are independent of liability insurance coverage. As a result, since the puzzle also holds in our french data, liability insurance cannot solely explain the puzzle.

Liquidity constraints It is natural to believe that liquidity constraints may play a role when wealth effects are considered. Indeed, relatively poor people may decide to turn down high coverage contracts because they may not have the available money to pay the corresponding insurance premium. Yet, remember that the insurance company allows its clients to smooth the premium over the year, up to monthly payments. Therefore, it is not very likely that the payment of the insurance premium cannot be made because the agent faces a liquidity constraint. Moreover, in the US data, a variable specifically captures the effect of a liquidity constraint [describe the variable]. As we also control for this variable in our regressions, we believe that it is fairly unlikely that our results may be due to liquidity constraints.

Adverse selection / moral hazard Consider the following argument. Under asymmetric information, there may be a separating equilibrium in which high-risk agents purchase full coverage, and low-risk agents purchase partial coverage. Hence, under positive correlation between wealth and the probability of being high-risk, wealthier individuals may more often choose a high coverage contract. This argument can thus explain that insurance is a normal good. We, however, suggest that this argument is of limited relevance for at least three reasons. The first reason is that there may be no or small information asymmetries in insurance markets (Chiappori and Salanié 2000). The second reason is that insurance companies, even under asymmetric information, must realize that wealthier individuals have more accidents, and then discriminate based on wealth [check whether it is not legally prohibited]. This may be especially easy in France when bancassurance is allowed, and the insurer has thus direct information about financial wealth. This should, in turn, make insurance coverage for the wealthy more costly, and depress insurance demand. The last reason is that it is usually observed that wealthier individuals invest more, and not less, in prevention efforts (Hammitt et al. 2000). Thus wealthier individuals may more likely be low-risk than high-risk agents.

Heterogenous risk aversion Our empirical analysis assumes that risk preferences are homogenous. Specifically, the problem may be that risk preferences are heterogenous and that they might be correlated with wealth. Although it is not very common to assume such a correlation, it can explain the result. Indeed, relatively rich people may decide to purchase more insurance because they are, for a given wealth, more risk averse than poor people. This may counteract the DARA effect. However, this hypothesis is quite implausible since it is usually found that rich people are more tolerant to risk (Guiso and Paella 2005). Moreover, this would contradict, again, our other result that the investment in risky assets increases with wealth.

Overall, we conclude that none of the advanced explanations based on standard theory is very convincing at explaining the puzzle. We next discuss possible behavioral explanations.

7.2 Behavioral theories

In what follows, we discuss whether alternative theories relying on bounded rationality and psychological aspects may explain the puzzle.

Prospect theory / loss aversion. A common starting point in behavioral decision making under risk is to consider prospect theory (Kahneman and Tversky 1979). We want to explore in particular whether loss aversion could explain the puzzle. To do so, we would need that loss aversion varies differently with wealth depending on whether the agent is considering an insurance or a portfolio decision. Yet, we are not aware of such an extension of prospect theory to account specifically for the effects of wealth in different contexts.

Risk perception. Consider the following hypothesis. Suppose that the rich are systematically more optimistic than the poor about financial risks, but that they are more pessimistic about insurance risks. This hypothesis then would imply that the rich invest more in risky assets and in the same time demand more insurance than the poor, and hence it could explain the puzzle. However, we note first that we are not aware of any empirical analysis showing relative differences in risk perceptions of poor and rich, and in particular for the specific optimism/pessimism reversal hypothesis proposed here. Moreover, remember that our survey elicits some measures for objective/subjective risk perception, and thus somehow controls for biases in risk perceptions. Overall, we consider that this hypothesis is unlikely to be a main driver for explaining the puzzle.

Context-dependent preferences Our empirical analysis shows that risk taking increases in wealth for portfolio decisions but decreases in wealth for insurance decisions. We may argue that portfolio and insurance decisions concern different contexts, and that preferences differ in each context. Indeed, if for instance preferences are DARA in the financial context, and are IARA in the insurance context, this may explain the results. Although possible, we note that this hypothesis implies that risk preferences belong to a different family of utility functions in each specific context, which seems inconsistent with previous empirical findings in the behavioral risk taking literature (Barseghyan et al. 2011, Armantier and Treich 2016). The possibility that context-dependent risk preferences may explain the puzzle seems unlikely a priori.

Emotions Suppose that some people derive an extra value associated with the fact that their goods is well insured. For instance, people may enjoy the feeling of "peace of mind" (Chiappori and Salanié 2000, Kunreuther and Pauly 2005) associated with full insurance, as they do not face anymore the permanent fear associated with the possibility of losing something. Alternatively, suppose that some people attach a sentimental value to the goods they insure, that is a value that goes beyond the market value of the insured goods. In that case, it seems reasonable to assume that these people would be willing to pay more in order to receive a "consolation" if they loose the insured good, and thus in turn they would purchase more insurance for these goods. Both assumptions might explain the puzzle if it can be shown that the rich attach systematically a higher value for peace of mind or a higher sentimental value to the goods they insure than the poor. This is an open question left for future research.

- cost of time as a possible explanation for the puzzle?
- Guiso Sapienza and Zingales (2013) find evidence supporting Loewenstein (2001) hypothesis that investors react to fear of large losses, which would explain the observed increased in risk aversion after 2008 crisis. Would that explain excessive insurance by the wealthy?

- The insurance product is not properly defined, in particular it has unobserved (to us) characteristics that are valued more by the wealthy (e.g. quality of service).

Appendix A: Theoretical background

A.1 The simple insurance demand model

An agent with wealth$w$ faces a random loss$\tilde{L}$. The loss is insurable. The insurance contract is such that the agent receives an indemnityαL in case of loss L. The insurance premium is equal to$\alpha\pi$. The agent decides the level of coverageαwhich maximizes expected utility given a strictly increasing and concave utility function u. Formally,

$$max_{\alpha} Eu[w - \alpha\pi - (1-\alpha)\tilde{L}] \tag{2}$$

The model above can be rewritten

$$max_{a} Eu[w_0 + a\tilde{X}] \tag{3}$$

where $w_0 = w - \pi$, $a = 1 - \alpha$ and $\tilde{X} = (\pi - \tilde{L})$. The purpose of this change in notations is to show that the insurance demand model is isomorphic to the portfolio decision model, as is well known (Gollier 2001). In the portfolio model,a is interpreted as the investment in (net) risky asset, and the optimal solution is characterized by

$$E\tilde{X}u'[w_0 + a\tilde{X}] = 0 \tag{4}$$

Note that the left hand side is positive when $a = 0$ iff$E\tilde{X} > 0$. Therefore, we have$a > 0$ iff the expected value of the risky asset is positive$E\tilde{X} > 0$ (Pratt 1964). Equivalently, we have less than full insurance,$\alpha < 1$, as soon as insurance is not actuarially fair, i.e. $\pi > E\tilde{L}$.

We now turn to the main hypothesis underlying our results, namely to wealth effects. It is well known that$a$ increases in wealthw_0 iff$u$ is DARA. Indeed, using standard comparative statics techniques, a increases in w_0 iff $E\tilde{X}u'[w_0+a\tilde{X}]$ increases inw_0 at the optimal solution, namely iff $E\tilde{X}u'[w_0 + a\tilde{X}] = 0$ implies$-E\tilde{X}u''[w_0 + a\tilde{X}] \leq 0$. This implication means that an agent with utility$-u'$ is willing to invest less in the risky asset than an agent with utility u, or equivalently that$-u'$ is more risk averse than u. This is exactly equivalent to DARA, namely to $\frac{-u''(w)}{u'(w)}$ decreasing in w. Using the isomorphism between portfolio and insurance decisions, this result also implies that the optimal insurance coverageαdecreases in wealth iff u is DARA (Mossin 1968).

A.2 Insurance and portfolio decisions

We now consider a model in which insurance and the portfolio decisions are made simultaneously. Using the notations above, we have

$$max_{a,b} Eu[w + a\tilde{X} + b\tilde{Y}] \tag{5}$$

We want to analyze how the optimal solutions a and b vary with w. This comparative statics analysis with multiple decisions is difficult in the general. Here, we only consider "small risks" (Samuelson 1970). Assuming "small risks" imposes a strong restriction on the admissible set of probability distributions. This set, however, includes various standard probability distributions such as Normal distributions or Brownian processes. This restriction implies that a second-order approximation is valid in the sense that it leads to the same solution as the general problem (3), that is

$$Eu[w_0 + a\tilde{X} + b\tilde{Y}] \simeq u(w) + E\{a\tilde{X} + b\tilde{Y}\}u'(w) + \frac{1}{2!}E\{a\tilde{X} + b\tilde{Y}\}^2 u''(w)$$

Differentiating the right hand side of the last equation with respect to a and equating to zero gives

$$a = \frac{E\tilde{X}}{E\tilde{X}^2}\frac{u'(w)}{-u''(w)} - b\frac{E\tilde{X}\tilde{Y}}{E\tilde{X}^2} \tag{6}$$

We assume that the risks$\tilde{X}$ and$\tilde{Y}$ are independent, with $E\tilde{X} > 0$ and $E\tilde{Y} > 0$. With these assumptions, note then that the above expression shows that a is reduced due to the portal decision$b$. This effect can be interpreted as a background risk effect induced by the portfolio decision b. Exhibiting a similar expression as (6) for b, and solving for these two equations, we can then obtain:

$$a = \frac{E\tilde{X}}{E\tilde{X}^2}\frac{u'(w)}{-u''(w)}[\frac{E\tilde{Y}^2 - (E\tilde{Y})^2}{E\tilde{Y}^2 - \frac{(E\tilde{X})^2}{E\tilde{X}^2}(E\tilde{Y})^2}] \tag{7}$$

Observe that since $\frac{(E\tilde{X})^2}{E\tilde{X}^2}$ is lower than one, the expression into bracket in (7) is positive. This shows that a is positive, and increases with wealth iff $\frac{u'(w)}{-u''(w)}$increases with wealth, that is iff DARA. This implies that the portfolio decision increases with wealth under DARA. Equivalently, using again the isomorphism between insurance and portfolio decisions presented above, this shows that the optimal insurance decreases with wealth iff DARA. Hence, the standard results about the effects of wealth on the insurance and portfolio decisions when the decisions are made separately (see A.1) also hold when the insurance and portfolio decisions are made simultaneously (at least when the risks are small).

A.3 Insurance and savings decisions

We now study a model in which savings and insurance decisions are made simultaneously. We consider the following simple model

$$max_{s,a} u(w - s) + Eu[s + a\tilde{X}] \tag{8}$$

where$s$ is savings. In this model, the solutions, denoted $s(w)$and $a(w)$, are characterized by

$$-u'(w - s(w)) + Eu'[s(w) + a\tilde{X}] = 0$$

$$E\tilde{X}u'[s(w) + a(w)\tilde{X}] = 0$$

Differentiating the last equation with respect to w, we obtain

$$a'(w) = s'(w)\frac{E\tilde{X}u''[s(w) + a(w)\tilde{X}]}{-E\tilde{X}^2u''[s(w) + a(w)\tilde{X}]}$$

This last equality shows that $a'(w)$ has the sign of $s'(w)$ iff $E\tilde{X}u''[s(w)+a\tilde{X}] \geq 0$.Yet we have seen above in Appendix A.1 that $E\tilde{X}u'[s(w)+a(w)\tilde{X}] = 0$ implies $E\tilde{X}u''[s(w)+a(w)\tilde{X}] \geq 0$ iff DARA. Hence, if savings is a normal good, insurance demand decreases in wealth iff DARA, as in the simple insurance demand model (2). This implies that the effect of the level of savings on insurance demand is positive iff DARA. Moreover, we note that Aura et al. (2002) show that savings is indeed always a normal good in a similar savings-portfolio model, and derive a similar result that wealth increases investments in risky assets iff DARA. They also generalize the result to multiple portfolio decisions, and thus to the case in which savings and both insurance and portfolio decisions are made simultaneously.

A.4 Insurance demand with wealth-dependent loss

Next, we consider a model in which the loss may depend on wealth. For simplicity, we assume that the distribution of the loss is binary, that is, either the agent looses $L(w)$ with probability p or he looses nothing. Note that the loss is now denoted$L(w)$, and thus we make explicit the fact that the loss is wealth-dependent. Also, for simplicity, we assume that the insurance premium now takes the standard form$\alpha\pi = (1 + \lambda)\alpha pL(w)$, where $\lambda > 0$ is the loading factor. Given these assumptions, the model (2) can be rewritten as follows:

$$max_{\alpha}(1 - p)u(w - (1 + \lambda)\alpha pL(w)) + pu(w - (1 + \lambda)\alpha pL(w) - (1 - a)L(w))$$

Let us consider a common CRRA utility function, $u(w) = (1-\gamma)^{-1}(w^{1-\gamma})$. In this case, the problem of the agent can be rewritten

$$max_{\alpha}(1-\gamma)^{-1}\{(1-p)[\frac{w}{L(w)}-(1+\lambda)p\alpha]^{1-\gamma}+p[\frac{w}{L(w)}-(1+\lambda)p\alpha-(1-\alpha)]^{1-\gamma}\}$$

which is equivalent to a standard problem of insurance demand with a "fixed" loss (i.e., a loss independent from wealth and equal to 1 in that case) and an initial wealth equal to $\frac{w}{L(w)}$. Therefore, since the CRRA utility function displays DARA, it is immediate that the effect of wealth on insurance demand is fully determined by how $\frac{w}{L(w)}$ varies with w. If $L(w)$ is linear in w for instance, as is the case for liability insurance (i.e., $L(w) = w$), then wealth has no effect on insurance coverage. More generally, the effect of wealth is negative iff the elasticity of the insured good with respect to wealth, i.e. $\frac{wL'(w)}{L(w)}$, is lower than 1.

We can obtain a closed-form solution in the case $u(w) = log(w)$ (i.e., $\gamma \to 1$). Indeed, in that case, we can express the demand for insurance, in money amounts, as follows:

$$a(w)L(w) = L(w)\frac{1-p}{1-p-\lambda p} - w\frac{\lambda}{(1+\lambda)(1-\lambda-\lambda p)}$$

This right hand side of this expression illustrates the two effects of wealth on insurance demand, the one related to the wealth-dependent loss and the one related to risk preferences. In the standard insurance demand model, since$L(w)$ does not depend on w, the effect of wealth on insurance demand is only determined by second term of the right hand side due to$a(w)$ only, and indeed decreases with wealth since the log utility function displays DARA. Yet, the first term may increase in wealth, so that the effect of wealth on insurance demand is globally ambiguous. Under liability insurance, i.e., $L(w) = w$, the first effect always dominates, and wealthier agents always pay more in order to insure for the loss of their wealth (Szpiro 1986).

Appendix 1: Glossary

*Objective risk = 0 if no damage in the past 2 years, = 1 if 0< damage past 2 year <1,500, = 2 if damage past 2 years >1500 .).

*Objective risk = 0 if no damage in the past 2 years, = 1 if 0< damage past 2 year <1,500, = 2 if damage past 2 years >1500 .

Liquid Wealth = investments + assets + retirement wealth - non housing debt . *Financial Wealth = Liquid wealth + NET Homes + Business shares . *Dollar Risky Liquid = stock + mutual funds . *Dollar Risky Financial = Dollar Risky liquid + Homes + share in Business

. . . *Low Numeracy = 1 when respondent gets 3 (or less) out of 6 literacy and numeracy questions correct .

*Zip Density = Population density in the respondent's zip code in thousand .

*Know car insurance = qualitative variable between 1 (know nothing) and 7 (know very well) .

*Know savings and Debt = qualitative variable between 1 (know nothing) and 5 (know very well) .

*

*Subjective risk = 0 if damage in next 2 years <300, = 1 if 300< damage next 2 years <1,500, = 2 if damage next 2 years >1500 .

*Risk attitude = qualitative variable between 1 (I do not take any risk) and 7 (I take a lot of risk) (Dohmen et al. question) .

*Chance get 2k = reported probability to come up with $2k if the need arose (generally considered a measure of liquidity or financial fragility) .

*Expected stock change = Expected change in US stock market over the next 12 months in % .

*Education: 1 = High school or less, 2 = some college, 3 = BA or more .

*Credit Score: 1 = <620, 2 = 620-679, 3 = 680-719, 4 = 720:760, 5 = >760 .

Table 1: Demographic Characteristics									
	Data 2015 & 2016 (N=1,811)			Data 2015 (N=898)			Data 2016 (N=913)		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Age	49.32	49.00	15.47	49.39	49.00	15.42	49.24	49.00	15.52
Gender (Female=1)	0.48	0.00	0.50	0.47	0.00	0.50	0.49	0.00	0.50
Married	0.65	1.00	0.48	0.65	1.00	0.48	0.65	1.00	0.48
Have children	0.39	0.00	0.49	0.37	0.00	0.48	0.41	0.00	0.49
Education	1.96	2.00	0.74	1.97	2.00	0.75	1.96	2.00	0.73
Risk tolerance	3.66	4.00	1.66	3.67	4.00	1.71	3.64	4.00	1.62
Financial liquidity	0.76	0.99	0.33	0.76	0.99	0.33	0.77	0.99	0.33
Low financial literacy	0.27	0.00	0.44	0.28	0.00	0.45	0.26	0.00	0.44
Zip density (in 1,000)	3.41	1.46	7.82	3.39	1.42	8.27	3.44	1.55	7.33
Credit score	3.80	4.00	1.42	3.79	4.00	1.42	3.81	4.00	1.43

Education: 1 = Less than BA, 2 = BA, 3 = More than BA (e.g. Master, Doctorate, Professional degree).
Risk tolerance = Qualitative measure (from Dohmen et al. 2011) of willingness to risk regarding financial matters between 1 (not willing at all) and 7 (very willing).
Financial liquidity = Reported percent chance to come up with $2k if the need arose.
Low financial literacy = 1 when respondent gets fewer than 4 out of 6 financial literacy questions correct.
Zip density = Population density in the respondent's zip code (in 1,000).
Credit score: 1 = <620, 2 = between 620 and 679, 3 = between 680 and 719, 4 = between 720 and 760, 5 = >760.

Table 2: Components of Liquid Wealth									
	Data 2015 & 2016			Data 2015			Data 2016		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Retirement savings†	217.12	81.80	353.67	209.45	75.00	335.32	224.82	91.00	371.27
Savings & investments†	95.69	17.00	272.71	91.90	16.50	291.47	99.36	18.00	253.30
Other Assets†	76.54	24.00	159.82	75.14	23.50	157.01	77.94	24.00	162.65
Non-housing debt†	43.42	20.00	76.30	41.56	20.00	65.15	45.22	20.00	85.72
Liquid wealth†	280.01	83.00	552.96	272.60	73.00	544.89	287.32	98.40	561.01
Share of liquid risky assets	0.34	0.30	0.23	0.32	0.26	0.23	0.36	0.33	0.23

† In $1,000.
Retirement savings = Money on IRA, 401K, thrift, savings plan.
Savings and investments = Money on checking and savings accounts, CDs, stocks, bonds, mutual funds, Treasury bonds.
Other assets = Jewelry, valuable collection(s), vehicles, cash value in a life insurance policy, rights in a trust or estate.
Non-housing debt = Balances on credit cards, auto loans, student loans, personal loans, medical or legal bills.
Share of liquid risky assets = Proportion of liquid assets owned in stocks and mutual funds.
Except for the next to last row (Liquid wealth), all statistics are conditional on the variable being strictly greater than 0.

Table 3: Components of Financial Wealth									
	Data 2015 & 2016			Data 2015			Data 2016		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Primary home value†	268.52	185.00	240.71	265.87	180.00	227.02	271.18	190.00	253.94
Home equity†	198.50	122.00	242.55	196.57	110.00	238.60	200.46	130.00	246.65
Housing debt†	156.01	120.00	131.24	157.23	125.00	128.00	154.80	120.00	134.56
Business equity†	133.42	80.00	171.97	124.37	75.00	197.75	142.58	100.00	141.84
Financial wealth†	427.47	135.00	713.74	419.95	112.40	711.86	434.89	144.35	715.89
Share of financial risky assets	0.62	0.64	0.23	0.62	0.63	0.24	0.62	0.64	0.23

† In $1,000.
Primary home Value = Self-reported value of primary home (if it were sold today)
Home equity = Value of all homes minus all outstanding mortgages.
Housing debt = Outstanding mortgages for all homes.
Financial wealth = Liquid wealth + home and business equity.
Share of financial risky assets = proportion of financial assets owned in stocks, mutual funds, homes and business.

Table 4: Auto Insurance									
	Data 2015 & 2016			Data 2015			Data 2016		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Car value†	15.09	12.00	14.20	15.07	12.0	12.86	15.12	12.0	15.40
Damage past 2 years (in $)	1518.57	0.00	7054.79	1496.88	0.00	7891.78	1539.61	0.00	6138.53
Damage expected next 2 years	1866.73	750.00	2842.36	1843.84	750.00	2919.08	1888.98	750.00	2767.22
Annual premium (in $)	994.34	900.00	582.28	979.79	900.00	590.19	1008.47	900.00	574.48
Liability component	1.61	2.00	0.55	1.58	2.00	0.56	1.63	2.00	0.54
Injury component	1.42	2.00	0.70	1.41	2.00	0.70	1.44	2.00	0.70
Collision component	2.35	3.00	1.26	2.37	3.00	1.25	2.33	3.00	1.28
Comprehensive component	2.39	3.00	1.39	2.42	3.00	1.37	2.36	3.00	1.40
Uninsured component	1.92	2.00	1.40	1.93	2.00	1.41	1.92	2.00	1.39
Rental component	0.55	1.00	0.50	0.55	1.00	0.50	0.55	1.00	0.50
Towing component	0.59	1.00	0.49	0.59	1.00	0.49	0.59	1.00	0.49
Simple index $I_{i,1}$	4.32	4.75	1.75	4.32	4.75	1.76	4.32	4.75	1.75
Relative index (CDF) $I_{i,2}$	0.17	0.07	0.24	0.17	0.06	0.24	0.18	0.08	0.23
First component $I_{i,3}$	0.00	0.36	1.75	-0.01	0.35	1.77	0.01	0.36	1.74
Self-reported measure $I_{i,4}$	__	__	__	__	__	__	5.41	6.00	1.27

† In $1,000.
Liability: 0=No coverage, 1=Legal minimum, 2=More than legal minimum.
Injury: 0=No coverage, 1=Legal minimum, 2=More than legal minimum.
Collision: 0=No coverage, 1=deductible>$1,000, 2=$501<deductible<$1,000, 3=$251<deductible <=$500, 4=deductible<=$250.
Comprehensive: 0=No coverage, 1=deductible>$1,000, 2=$501<deductible<$1,000, 3=$251<deductible <=$500, 4=deductible<$250.
Uninsured: 0=No coverage, 1= Coverage<$10k, 2=$10k<coverage<$50k, 3=$50k<coverage<$100k, 4=Coverage>$100k.
Rental: 0=No coverage, 1=coverage.
Towing: 0=No coverage, 1=coverage.

Table 5: Correlation between Auto Insurance Indexes			
	Simple index $I_{i,1}$	Relative index (CDF) $I_{i,2}$	First component $I_{i,3}$
Relative index (CDF) $I_{i,2}$	0.72	__	__
First component $I_{i,3}$	0.96	0.70	__
Self-reported measure $I_{i,4}$	0.55	0.35	0.57

Table 6: Correlation with Auto Insurance Premium										
$I_{i,1}$	$I_{i,2}$	$I_{i,3}$	$I_{i,4}$	Liability	Injury	Collision	Comprehensive	Uninsured	Rental	Towing
0.23	0.18	0.24	0.21	0.03	0.05	0.10	0.08	0.02	0.11	0.08

Table 7: Homeowner Insurance									
	Data 2015 & 2016			Data 2015			Data 2016		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Replacement cost†	230.26	200.00	164.85	232.61	200.00	169.25	227.93	180.00	160.48
Annual premium (in $)	1,152.1	1,000.0	747.1	1,195.8	1,000.0	800.0	1,108.9	1,000.0	688.8
Damage past 2 years (in $)	1,221.2	0.0	6,959.3	1,062.9	0.0	4,411.5	1,377.4	0.0	8,777.9
Damage expected next 2 years	2,026.8	975.0	2,977.8	2,113.4	1,025.0	3,008.9	1,941.3	860.0	2,946.8
Deductible	2.27	2.00	0.63	2.31	2.00	0.64	2.24	2.00	0.62
Dwelling coverage†	215.09	180.00	166.30	218.57	194.50	171.16	211.65	165.00	161.42
Personal property coverage†	84.56	50.00	90.40	89.46	50.00	99.72	79.72	50.00	79.92
Liability coverage†	235.67	100.00	442.61	249.81	100.00	505.51	221.84	100.00	370.79
Have flood insurance	0.12	0.00	0.32	0.13	0.00	0.34	0.11	0.00	0.31
Have earth movement insurance	0.08	0.00	0.26	0.09	0.00	0.28	0.07	0.00	0.25
Have windstorm insurance	0.11	0.00	0.31	0.11	0.00	0.31	0.11	0.00	0.31
Have floater insurance	0.12	0.00	0.33	0.11	0.00	0.32	0.13	0.00	0.34
Have umbrella insurance	0.20	0.00	0.40	0.21	0.00	0.41	0.20	0.00	0.40
Simple index $I_{i,1}$	3.37	3.08	1.18	3.40	3.17	1.17	3.34	3.08	1.19

† In $1,000.

Replacement cost: amount it would cost today to rebuild home.

Deductible: 1 = <$250, 2 = $251 to $1,000, 3 = $1001 to $5,000, 4 >$5,000.

Dwelling (i.e. the home itself), personal property and liability coverages capture the maximum amount the insurance will pay in case of loss.

Earth movement insurance covers earthquake, mudslides, landslides and such.

Floater insurance covers special items such as expensive jewelry or antiques.

Umbrella insurance covers against lawsuit and claims.

Table 8: Baseline Model

Wealth = Liquid wealth, $I_{i,1}$ = Simple index of insurance coverage, R_i = Share of risky liquid assets

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i
Wealth ($100k)	0.699*** (0.072)	0.258*** (0.022)	0.699*** (0.073)	0.259*** (0.022)	0.614*** (0.069)	0.258*** (0.022)	0.418*** (0.066)	0.216*** (0.019)	0.397*** (0.060)	0.184*** (0.018)	0.435*** (0.058)	0.168*** (0.018)
Insurance Premium	—	—	0.030*** (0.010)	—	0.020* (0.012)	—	0.017 (0.012)	—	0.020* (0.012)	—	0.020 (0.013)	—
Car Value	—	—	—	—	0.022*** (0.004)	—	0.021*** (0.004)	—	0.015*** (0.004)	—	0.016*** (0.004)	—
Objective Risk Auto	—	—	—	—	0.127** (0.058)	—	0.106* (0.058)	—	0.050 (0.058)	—	0.050 (0.058)	—
Zip Density	—	—	—	—	-2.429 (8.861)	—	-0.168 (8.786)	-0.060 (1.079)	-1.364 (8.232)	-0.303 (1.081)	-0.310 (8.248)	-0.525 (1.121)
Age	—	—	—	—	—	—	0.015*** (0.003)	-0.003*** (0.001)	0.012*** (0.003)	-0.002** (0.001)	0.010*** (0.003)	-0.002** (0.001)
Gender	—	—	—	—	—	—	-0.051 (0.083)	-0.063*** (0.020)	0.109 (0.082)	-0.032 (0.020)	0.058 (0.083)	-0.011 (0.020)
Married	—	—	—	—	—	—	0.049 (0.092)	0.074*** (0.022)	-0.035 (0.088)	0.050** (0.022)	-0.038 (0.088)	0.052** (0.021)
Have Kids	—	—	—	—	—	—	0.068 (0.086)	0.021 (0.021)	0.087 (0.081)	0.032 (0.020)	0.109 (0.081)	0.022 (0.020)
Black	—	—	—	—	—	—	-0.015 (0.160)	-0.062 (0.039)	-0.010 (0.153)	-0.014 (0.040)	0.007 (0.150)	-0.029 (0.039)
Latino	—	—	—	—	—	—	-0.283* (0.165)	-0.025 (0.037)	-0.230 (0.160)	-0.009 (0.037)	-0.218 (0.159)	-0.014 (0.037)
Unemployed	—	—	—	—	—	—	-0.185 (0.286)	-0.066 (0.064)	-0.292 (0.283)	-0.044 (0.062)	-0.246 (0.287)	-0.067 (0.060)
High Education	—	—	—	—	—	—	0.234** (0.091)	0.094*** (0.022)	0.176** (0.088)	0.073*** (0.022)	0.182** (0.088)	0.070*** (0.021)
Low Education	—	—	—	—	—	—	-0.358*** (0.098)	-0.112*** (0.023)	-0.284*** (0.097)	-0.080*** (0.023)	-0.308*** (0.096)	-0.073*** (0.023)
Credit Score	—	—	—	—	—	—	0.055* (0.034)	0.050*** (0.008)	0.021 (0.032)	0.031*** (0.008)	0.018 (0.032)	0.033*** (0.008)
Subjective Risk Auto	—	—	—	—	—	—	—	—	0.164*** (0.047)	—	0.167*** (0.047)	—
Subjective Risk Stock	—	—	—	—	—	—	—	—	—	0.305** (0.124)	—	0.303** (0.127)
Low Financial Literacy	—	—	—	—	—	—	—	—	-0.240** (0.098)	-0.085*** (0.024)	-0.243** (0.097)	-0.076*** (0.024)
Know Car Insurance	—	—	—	—	—	—	—	—	0.264*** (0.027)	—	0.269*** (0.027)	—
Know Savings and Debts	—	—	—	—	—	—	—	—		0.030** (0.012)	—	0.020* (0.012)
Financial Liquidity	—	—	—	—	—	—	—	—	0.467*** (0.136)	0.261*** (0.035)	0.528*** (0.136)	0.234*** (0.035)
Risk Tolerance	—	—	—	—	—	—	—	—	—	—	-0.089*** (0.025)	0.041*** (0.006)
Constant	4.121*** (0.048)	-0.052*** (0.013)	3.823*** (0.114)	-0.052*** (0.013)	3.650*** (0.125)	-0.052*** (0.013)	2.724*** (0.252)	-0.151*** (0.052)	1.462*** (0.276)	-0.350*** (0.062)	1.790*** (0.287)	-0.488*** (0.066)
Correlation (ρ_{IR})	0.109*** (0.028)		0.115*** (0.028)		0.095*** (0.028)		0.083** (0.028)		0.076** (0.028)		0.073** (0.028)	
Observations	1811		1811		1811		1806		1806		1806	
AIC	8816.0		8799.1		8742.3		8483.6		8306.6		8248.0	

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Alternative Measures of Insurance Coverage

Wealth = Liquid wealth, R_i = Share of risky liquid assets

	Model 1†		Model 2†		Model 3†		Model 4†		Model 5†		Model 6†	
	$I_{i,2}$	R_i	$I_{i,3}$	R_i	$I_{i,4}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{\overline{i,1}}$	R_i
Wealth ($100k)	0.077***	0.167***	0.439***	0.168***	0.317***	0.168***	0.451***	0.160***	0.432***	0.181***	0.279***	0.167***
	(0.016)	(0.018)	(0.058)	(0.018)	(0.051)	(0.018)	(0.073)	(0.019)	(0.085)	(0.021)	(0.062)	(0.018)
Insurance Premium	0.001*	—	0.019	—	0.016*	—	0.022	—	0.016	—	0.014	—
	(0.001)		(0.013)		(0.010)		(0.018)		(0.020)		(0.011)	
Car Value	0.001***	—	0.016***	—	0.013***	—	0.016***	—	0.015**	—	0.009***	—
	(0.001)		(0.004)		(0.003)		(0.005)		(0.006)		(0.003)	
Objective Risk Auto	-0.002	—	0.061	—	0.045	—	0.046	—	0.062	—	-0.024	—
	(0.008)		(0.058)		(0.047)		(0.081)		(0.088)		(0.056)	
Zip Density	0.323	-0.557	-0.401	-0.523	-1.435	-0.531	5.342	0.316	8.193	0.344	8.531	-0.546
	(1.349)	(1.125)	(8.240)	(1.121)	(6.681)	(1.121)	(9.449)	(1.748)	(9.747)	(1.792)	(5.415)	(1.123)
Age	0.001**	-0.002**	0.010***	-0.002**	0.010***	-0.002**	0.011***	-0.002**	0.009**	-0.003**	0.007**	-0.002**
	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)
Gender	-0.010	-0.012	0.054	-0.011	0.101	-0.011	-0.016	-0.006	-0.045	-0.005	0.130	-0.012
	(0.012)	(0.020)	(0.083)	(0.020)	(0.068)	(0.020)	(0.114)	(0.026)	(0.128)	(0.030)	(0.084)	(0.020)
Married	-0.002	0.052**	0.002	0.052**	-0.051	0.052**	-0.066	0.056**	0.009	0.049*	0.112	0.052**
	(0.012)	(0.021)	(0.089)	(0.021)	(0.072)	(0.021)	(0.119)	(0.027)	(0.137)	(0.030)	(0.095)	(0.021)
Have Kids	0.015	0.022	0.096	0.022	0.102	0.022	0.152	0.013	0.202*	0.022	0.127	0.022
	(0.012)	(0.020)	(0.081)	(0.020)	(0.067)	(0.020)	(0.107)	(0.025)	(0.122)	(0.029)	(0.087)	(0.020)
Black	0.009	-0.029	-0.051	-0.029	0.088	-0.029	0.141	0.005	0.027	-0.015	0.076	-0.029
	(0.019)	(0.039)	(0.152)	(0.039)	(0.123)	(0.039)	(0.199)	(0.048)	(0.238)	(0.059)	(0.180)	(0.039)
Latino	-0.003	-0.014	-0.260	-0.014	-0.087	-0.014	-0.129	-0.039	-0.185	-0.043	0.108	-0.014
	(0.022)	(0.036)	(0.161)	(0.037)	(0.132)	(0.036)	(0.206)	(0.045)	(0.227)	(0.049)	(0.147)	(0.036)
Unemployed	-0.011	-0.067	-0.221	-0.068	-0.260	-0.067	-0.456	-0.091	-0.572	-0.104	-0.113	-0.067
	(0.033)	(0.060)	(0.287)	(0.060)	(0.227)	(0.060)	(0.401)	(0.083)	(0.503)	(0.101)	(0.350)	(0.060)
High Education	0.025*	0.070***	0.196**	0.070***	0.147**	0.070***	0.242**	0.074***	0.238*	0.084***	0.225**	0.070***
	(0.014)	(0.021)	(0.087)	(0.021)	(0.073)	(0.021)	(0.119)	(0.027)	(0.137)	(0.032)	(0.091)	(0.021)
Low Education	-0.032***	-0.073***	-0.327***	-0.073***	-0.205**	-0.073***	-0.324**	-0.062**	-0.360**	-0.062**	-0.171*	-0.073***
	(0.012)	(0.023)	(0.097)	(0.023)	(0.080)	(0.023)	(0.129)	(0.028)	(0.145)	(0.030)	(0.098)	(0.023)
Credit Score	-0.000	0.033***	0.024	0.033***	-0.004	0.033***	0.035	0.033***	0.026	0.037***	0.040	0.033***
	(0.004)	(0.008)	(0.032)	(0.008)	(0.026)	(0.008)	(0.042)	(0.010)	(0.047)	(0.011)	(0.033)	(0.008)
Subjective Risk Auto	0.016**	—	0.170***	—	0.124***	—	0.152**	—	0.213***	—	0.125**	—
	(0.007)		(0.046)		(0.039)		(0.063)		(0.071)		(0.049)	
Subjective Risk Stock	—	0.300**	—	0.303**	—	0.304**	—	0.294**	—	0.327**	—	0.300**
		(0.116)		(0.117)		(0.117)		(0.139)		(0.152)		(0.126)
Low Financial Literacy	-0.031**	-0.075***	-0.242**	-0.075***	-0.196**	-0.076***	-0.265**	-0.063**	-0.424***	-0.079**	-0.230**	-0.075***
	(0.012)	(0.024)	(0.098)	(0.024)	(0.080)	(0.024)	(0.132)	(0.029)	(0.149)	(0.034)	(0.104)	(0.024)
Know Car Insurance	0.032***	—	0.268***	—	0.210***	—	0.254***	—	0.245***	—	0.227***	—
	(0.004)		(0.027)		(0.022)		(0.035)		(0.040)		(0.029)	
Know Savings and Debts	—	0.020*	—	0.020*	—	0.020*	—	0.028*	—	0.027	—	0.020*
		(0.012)		(0.012)		(0.012)		(0.015)		(0.017)		(0.012)
Financial Liquidity	0.033**	0.234***	0.585***	0.234***	0.350***	0.235***	0.516***	0.189***	0.665***	0.165***	0.330**	0.234***
	(0.016)	(0.035)	(0.137)	(0.035)	(0.112)	(0.035)	(0.186)	(0.045)	(0.215)	(0.051)	(0.148)	(0.035)
Risk Tolerance	-0.010***	0.041***	-0.089***	0.041***	-0.083***	0.041***	-0.089***	0.050***	-0.090**	0.046***	-0.090***	0.041***
	(0.003)	(0.006)	(0.025)	(0.006)	(0.021)	(0.006)	(0.033)	(0.008)	(0.038)	(0.009)	(0.030)	(0.006)
Constant	-0.069**	-0.487***	-2.562***	-0.488***	0.842***	-0.488***	1.757***	-0.514***	1.781***	-0.481***	3.324***	-0.487***
	(0.034)	(0.065)	(0.291)	(0.066)	(0.233)	(0.066)	(0.365)	(0.080)	(0.418)	(0.091)	(0.306)	(0.065)
Correlation (ρ_{IR})	0.077**		0.086**		0.079**		0.081**		0.086**		0.083**	
	(0.025)		(0.028)		(0.028)		(0.038)		(0.043)		(0.037)	
Observations	1806		1806		912		1025		798		1806	
AIC	1391.0		8235.4		7603.6		4703.1		3689.0		4471.1	

† **Model 1** : $I_{i,2}$ = Relative index (CDF); **Model 2** : $I_{i,3}$ = First component in principal component analysis; **Model 3** : $I_{i,4}$ = Self-reported measure of insurance coverage (for 2016 survey only); **Model 4** : Simple index $I_{i,1}$ for respondents in states with legal minima between 20/40/10 and 25/50/25; **Model 5** : Simple index $I_{i,1}$ for respondents in states with legal minima between 25/50/10 and 25/50/25; **Model 6** : $I_{\overline{i,1}}$ = Simple index $I_{i,1}$ absent any liability protection.

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Alternative Measures of Wealth and Investments in Risky Assets $I_{i,1}$ = Simple index of insurance coverage						
	Model 1†		Model 2†		Model 3†	
	$I_{i,1}$	$R_{i,1}$	$I_{i,1}$	$R_{i,2}$	$I_{i,1}$	$R_{i,3}$
Wealth ($100k)	0.337*** (0.047)	0.055*** (0.011)	0.441*** (0.059)	0.466*** (0.026)	0.343*** (0.047)	0.588*** (0.025)
Insurance Premium	0.021* (0.012)	—	0.020 (0.012)	—	0.020 (0.012)	—
Car Value	0.015*** (0.004)	—	0.016*** (0.004)	—	0.015*** (0.004)	—
Objective Risk Auto	0.047 (0.058)	—	0.051 (0.058)	—	0.051 (0.058)	—
Zip Density	-0.030 (8.281)	-2.000 (1.830)	-0.277 (8.253)	-0.226 (0.627)	-0.243 (8.304)	0.472 (1.255)
Age	0.010*** (0.003)	-0.001** (0.000)	0.010*** (0.003)	-0.002** (0.001)	0.010*** (0.003)	-0.002** (0.001)
Gender	0.061 (0.083)	-0.033* (0.020)	0.059 (0.083)	0.006 (0.011)	0.062 (0.083)	-0.009 (0.012)
Married	-0.049 (0.088)	0.084*** (0.022)	-0.040 (0.088)	0.010 (0.015)	-0.050 (0.088)	0.049*** (0.015)
Have Kids	0.110 (0.081)	0.032 (0.020)	0.110 (0.081)	0.007 (0.011)	0.110 (0.081)	0.030** (0.012)
Black	0.011 (0.150)	-0.079* (0.042)	0.007 (0.150)	-0.001 (0.019)	0.011 (0.150)	-0.022 (0.021)
Latino	-0.213 (0.159)	0.007 (0.040)	-0.214 (0.159)	0.008 (0.020)	-0.209 (0.159)	-0.003 (0.023)
Unemployed	-0.244 (0.288)	-0.052 (0.077)	-0.246 (0.287)	-0.034 (0.027)	-0.248 (0.288)	-0.050 (0.033)
High Education	0.171* (0.088)	0.042** (0.020)	0.180** (0.088)	0.037*** (0.013)	0.169* (0.088)	0.052*** (0.014)
Low Education	-0.302*** (0.096)	-0.054** (0.024)	-0.309*** (0.096)	-0.043*** (0.014)	-0.303*** (0.096)	-0.048*** (0.014)
Credit Score	0.016 (0.032)	0.026*** (0.008)	0.017 (0.032)	0.015*** (0.005)	0.016 (0.032)	0.015*** (0.005)
Subjective Risk Auto	0.169*** (0.047)	—	0.168*** (0.047)	—	0.169*** (0.047)	—
Subjective Risk Stock	—	0.238** (0.107)	—	0.301*** (0.104)	—	0.244** (0.101)
Low Financial Literacy	-0.244** (0.098)	-0.042* (0.025)	-0.213** (0.097)	-0.038*** (0.013)	-0.233** (0.098)	-0.030** (0.012)
Know Car Insurance	0.264*** (0.027)	—	0.269*** (0.027)	—	0.265*** (0.027)	—
Know Savings and Debts	—	0.024* (0.013)	—	0.026** (0.007)	—	0.013* (0.007)
Financial Liquidity	0.519*** (0.136)	0.185*** (0.038)	0.528*** (0.136)	0.099*** (0.021)	0.517*** (0.136)	0.103*** (0.022)
Risk Tolerance	-0.086*** (0.025)	0.003 (0.006)	-0.088*** (0.025)	0.019*** (0.004)	-0.086*** (0.025)	0.011*** (0.004)
Constant	1.791*** (0.288)	0.095 (0.074)	1.789*** (0.287)	-0.302*** (0.045)	1.795*** (0.288)	-0.147*** (0.042)
Correlation (ρ_{IR})	0.086** (0.027)		0.073** (0.026)		0.076** (0.024)	
Observations	1806		1806		1806	
AIC	8649.4		6870.5		6893.9	

† **Model 1** : Wealth = Financial Wealth, $R_{i,1}$ = Share of risky financial assets; **Model 2** : Wealth = Liquid Wealth, $R_{i,2}$ = Amount invested in risky liquid assets (in $100k); **Model 3** : Wealth = Financial Wealth, $R_{i,3}$ = Amount invested in risky financial assets (in $100k). Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Baseline Model for 2015 and 2016 Data

Wealth = Liquid wealth, $I_{i,1}$ = Simple index of insurance coverage, R_i = Share of risky liquid assets

	2015 & 2016 Data		2015 Data		2016 Data	
	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i
Wealth ($100k)	0.435*** (0.058)	0.168*** (0.018)	0.446*** (0.074)	0.134*** (0.020)	0.436*** (0.091)	0.108*** (0.016)
Insurance Premium	0.020 (0.013)	—	0.027 (0.021)	—	0.014 (0.014)	—
Car Value	0.016*** (0.004)	—	0.015*** (0.005)	—	0.016*** (0.005)	—
Objective Risk Auto	0.050 (0.058)	—	0.087 (0.087)	—	0.020 (0.074)	—
Zip Density	-0.310 (8.248)	-0.525 (1.121)	-10.530 (12.756)	-1.213 (0.758)	6.697 (9.740)	-0.599 (1.430)
Age	0.010*** (0.003)	-0.002** (0.001)	0.011*** (0.004)	-0.001* (0.001)	0.009** (0.004)	-0.001** (0.001)
Gender	0.058 (0.083)	-0.011 (0.020)	0.167 (0.119)	-0.004 (0.019)	-0.049 (0.115)	-0.023 (0.019)
Married	-0.038 (0.088)	0.052** (0.021)	-0.045 (0.125)	0.040** (0.019)	-0.031 (0.127)	0.041* (0.021)
Have Kids	0.109 (0.081)	0.022 (0.020)	0.100 (0.115)	0.006 (0.017)	0.123 (0.116)	0.027 (0.020)
Black	0.007 (0.150)	-0.029 (0.039)	-0.092 (0.212)	-0.006 (0.034)	0.100 (0.216)	-0.072** (0.036)
Latino	-0.218 (0.159)	-0.014 (0.037)	-0.332 (0.213)	0.006 (0.029)	-0.105 (0.234)	-0.022 (0.038)
Unemployed	-0.246 (0.287)	-0.067 (0.060)	-0.065 (0.348)	-0.053 (0.043)	-0.469 (0.471)	-0.029 (0.061)
High Education	0.182** (0.088)	0.070*** (0.021)	0.175* (0.105)	0.041** (0.020)	0.198* (0.106)	0.051** (0.023)
Low Education	-0.308*** (0.096)	-0.073*** (0.023)	-0.285** (0.138)	-0.045** (0.019)	-0.329** (0.134)	-0.049** (0.021)
Credit Score	0.018 (0.032)	0.033*** (0.008)	0.029 (0.049)	0.019*** (0.007)	0.007 (0.044)	0.020*** (0.007)
Subjective Risk Auto	0.167*** (0.047)	—	0.167** (0.065)	—	0.166** (0.068)	—
Subjective Risk Stock	—	0.303** (0.127)	—	0.289*** (0.084)	—	0.287*** (0.111)
Low Financial Literacy	-0.243** (0.097)	-0.076*** (0.024)	-0.312** (0.142)	-0.042** (0.019)	-0.324** (0.134)	-0.048** (0.023)
Know Car Insurance	0.269*** (0.027)	—	0.242*** (0.038)	—	0.292*** (0.039)	—
Know Savings and Debts	—	0.020* (0.012)	—	0.018 (0.012)	—	0.024** (0.011)
Financial Liquidity	0.528*** (0.136)	0.234*** (0.035)	0.621*** (0.197)	0.154*** (0.027)	0.427** (0.191)	0.156*** (0.032)
Risk Tolerance	-0.089*** (0.025)	0.041*** (0.006)	-0.080** (0.035)	0.028*** (0.005)	-0.095*** (0.037)	0.014** (0.006)
Constant	1.790*** (0.287)	-0.488*** (0.066)	1.635*** (0.402)	-0.217*** (0.057)	1.982*** (0.409)	-0.179*** (0.060)
Correlation (ρ_{IR})	0.073** (0.028)		0.070** (0.033)		0.081** (0.035)	
Observations	1806		894		912	
AIC	8248.0		3467.1		3764.1	

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Non Linear Wealth Effects

Wealth = Liquid wealth, R_i = Share of risky liquid assets

	Baseline Model			Model 1			Model 2			Model 3	
	$I_{i,1}$	R_i		$I_{i,1}$	R_i		$I_{i,1}$	R_i		$I_{i,1}$	R_i
Wealth ($100k)	0.435***	0.168***	**Ln Wealth**	392.935***	151.601***	**Wealth**	0.845***	0.633***	**Wealth 1st Quintile**	-0.854***	-0.354***
	(0.058)	(0.018)		(52.727)	(16.009)		(0.217)	(0.070)		(0.273)	(0.047)
	—	—		—	—	**Wealth Squared**	-0.301**	-0.255***	**Wealth 2nd Quintile**	-0.497**	-0.200***
							(0.146)	(0.043)		(0.231)	(0.032)
	—	—		—	—	**Wealth Cubed**	0.054**	0.035***	**Wealth 4th Quintile**	0.284	0.096***
							(0.023)	(0.006)		(0.194)	(0.027)
	—	—		—	—		—	—	**Wealth 5th Quintile**	0.800***	0.210***
										(0.304)	(0.026)
Insurance Premium	0.020	—		0.020	—		0.020	—		0.021*	—
	(0.013)			(0.013)			(0.013)			(0.013)	
Car Value	0.016***	—		0.015***	—		0.015***	—		0.015***	—
	(0.004)			(0.004)			(0.004)			(0.004)	
Objective Risk Auto	0.050	—		0.051	—		0.053	—		0.053	—
	(0.058)			(0.058)			(0.058)			(0.058)	
Zip Density	-0.310	-0.525		-0.302	-0.526		-0.319	-0.396		-0.332	-0.765
	(8.248)	(1.121)		(8.248)	(1.121)		(8.198)	(1.132)		(8.249)	(1.063)
Age	0.010***	-0.002**		0.008**	-0.002**		0.009***	-0.003**		0.010***	-0.004***
	(0.003)	(0.001)		(0.003)	(0.001)		(0.003)	(0.001)		(0.003)	(0.001)
Gender	0.058	-0.011		0.059	-0.010		0.062	-0.005		0.054	-0.005
	(0.083)	(0.020)		(0.085)	(0.020)		(0.083)	(0.019)		(0.083)	(0.019)
Married	-0.038	0.052**		-0.040	0.053**		-0.046	0.031		-0.063	0.028
	(0.088)	(0.021)		(0.088)	(0.021)		(0.088)	(0.021)		(0.089)	(0.021)
Have Kids	0.109	0.022		0.113	0.021		0.107	0.022		0.102	0.016
	(0.081)	(0.020)		(0.080)	(0.020)		(0.081)	(0.019)		(0.082)	(0.019)
Black	0.007	-0.029		0.008	-0.030		0.007	-0.027		0.010	-0.018
	(0.150)	(0.039)		(0.146)	(0.040)		(0.150)	(0.039)		(0.149)	(0.040)
Latino	-0.218	-0.014		-0.222	-0.014		-0.218	-0.006		-0.237	-0.013
	(0.159)	(0.037)		(0.160)	(0.038)		(0.159)	(0.036)		(0.159)	(0.037)
Unemployed	-0.246	-0.067		-0.245	-0.066		-0.252	-0.076		-0.272	-0.085*
	(0.287)	(0.060)		(0.291)	(0.060)		(0.287)	(0.056)		(0.283)	(0.050)
High Education	0.182**	0.070***		0.179**	0.071***		0.189**	0.072***		0.194**	0.071***
	(0.088)	(0.021)		(0.085)	(0.022)		(0.088)	(0.021)		(0.089)	(0.021)
Low Education	-0.308***	-0.073***		-0.312***	-0.074***		-0.300***	-0.058***		-0.276***	-0.054**
	(0.096)	(0.023)		(0.098)	(0.023)		(0.097)	(0.022)		(0.096)	(0.022)
Credit Score	0.018	0.033***		0.022	0.031***		0.012	0.028***		0.007	0.017**
	(0.032)	(0.008)		(0.030)	(0.008)		(0.032)	(0.008)		(0.032)	(0.008)
Subjective Risk Auto	0.167***			0.160***	—		0.164***	—		0.156***	—
	(0.047)			(0.051)			(0.047)			(0.047)	
Subjective Risk Stock	—	0.303**			0.298**			0.307**			0.427***
		(0.127)			(0.126)			(0.125)			(0.101)
Low Financial Literacy	-0.243**	-0.076***		-0.235**	-0.075***		-0.241**	-0.076***		-0.247**	-0.074***
	(0.097)	(0.024)		(0.096)	(0.025)		(0.097)	(0.023)		(0.097)	(0.023)
Know Car Insurance	0.269***	—		0.265***	—		0.268***	—		0.263***	—
	(0.027)			(0.028)			(0.027)			(0.027)	
Know Savings and Debts	—	0.020*			0.021*			0.016			0.020*
		(0.012)			(0.012)			(0.012)			(0.011)
Financial Liquidity	0.528***	0.234***		0.507***	0.236***		0.492***	0.176***		0.401***	0.117***
	(0.136)	(0.035)		(0.143)	(0.035)		(0.139)	(0.034)		(0.144)	(0.035)
Risk Tolerance	-0.089***	0.041***		-0.091***	0.042***		-0.090***	0.038***		-0.087***	0.037***
	(0.025)	(0.006)		(0.026)	(0.011)		(0.025)	(0.006)		(0.025)	(0.006)
Constant	1.790***	-0.488***		-2671.54***	-1031.90***		1.847***	-0.396***		2.177***	-0.129*
	(0.287)	(0.066)		(358.691)	(108.903		(0.289)	(0.066)		(0.322)	(0.071)
Correlation (ρ_{IR})	0.073**			0.075**			0.073**			0.074**	
	(0.028)			(0.028)			(0.028)			(0.029)	
Observations	1806			1806			1806			1806	
AIC	8248.0			8243.9			8180.7			8226.6	

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: IV Estimates

Wealth = Liquid wealth, $I_{i,1}$ = Simple index of insurance coverage, R_i = Share of risky liquid assets

	Baseline Model		Model 1		Model 2		Model 3	
	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i
Wealth ($100k)	0.435*** (0.058)	0.168*** (0.018)	0.297*** (0.054)	0.136*** (0.013)	0.228*** (0.048)	0.090*** (0.011)	0.327*** (0.055)	0.135*** (0.013)
Insurance Premium	0.020 (0.013)	—	0.020 (0.013)	—	0.021* (0.013)	—	0.021 (0.013)	—
Car Value	0.016*** (0.004)	—	0.016*** (0.004)	—	0.016*** (0.004)	—	0.016*** (0.004)	—
Objective Risk Auto	0.050 (0.058)	—	0.054 (0.058)	—	0.051 (0.058)	—	0.051 (0.058)	—
Zip Density	-0.310 (8.248)	-0.525 (1.121)	-0.779 (8.391)	-0.891 (1.137)	0.146 (8.466)	-0.521 (1.139)	-0.189 (8.418)	-0.657 (1.128)
Age	0.010*** (0.003)	-0.002** (0.001)	0.011*** (0.003)	-0.002** (0.001)	0.012*** (0.003)	-0.001* (0.001)	0.011*** (0.003)	-0.001** (0.001)
Gender	0.058 (0.083)	-0.011 (0.020)	0.053 (0.083)	-0.011 (0.020)	0.058 (0.083)	-0.008 (0.020)	0.059 (0.083)	-0.008 (0.020)
Married	-0.038 (0.088)	0.052** (0.021)	-0.039 (0.088)	0.051** (0.021)	-0.024 (0.088)	0.059*** (0.022)	-0.036 (0.088)	0.053** (0.021)
Have Kids	0.109 (0.081)	0.022 (0.020)	0.109 (0.082)	0.024 (0.020)	0.121 (0.082)	0.027 (0.020)	0.119 (0.082)	0.027 (0.020)
Black	0.007 (0.150)	-0.029 (0.039)	0.008 (0.151)	-0.030 (0.039)	-0.002 (0.151)	-0.036 (0.040)	0.007 (0.151)	-0.032 (0.039)
Latino	-0.218 (0.159)	-0.014 (0.037)	-0.227 (0.160)	-0.015 (0.037)	-0.220 (0.159)	-0.017 (0.037)	-0.215 (0.159)	-0.013 (0.037)
Unemployed	-0.246 (0.287)	-0.067 (0.060)	-0.245 (0.292)	-0.067 (0.060)	-0.247 (0.297)	-0.068 (0.065)	-0.237 (0.296)	-0.063 (0.062)
High Education	0.182** (0.088)	0.070*** (0.021)	0.194** (0.088)	0.074*** (0.021)	0.203** (0.088)	0.078*** (0.022)	0.193** (0.088)	0.074*** (0.022)
Low Education	-0.308*** (0.096)	-0.073*** (0.023)	-0.311*** (0.097)	-0.074*** (0.023)	-0.293*** (0.097)	-0.068*** (0.023)	-0.302*** (0.097)	-0.071*** (0.023)
Credit Score	0.018 (0.032)	0.033*** (0.008)	0.025 (0.032)	0.036*** (0.008)	0.026 (0.032)	0.036*** (0.008)	0.023 (0.032)	0.035*** (0.008)
Subjective Risk Auto	0.167*** (0.047)	—	0.166*** (0.047)	—	0.168*** (0.047)	—	0.169*** (0.047)	—
Subjective Risk Stock	—	0.303** (0.127)	—	0.302** (0.125)	—	0.420*** (0.133)	—	0.299** (0.125)
Low Financial Literacy	-0.243** (0.097)	-0.076*** (0.024)	-0.245** (0.098)	-0.075*** (0.024)	-0.258*** (0.098)	-0.082*** (0.024)	-0.239** (0.098)	-0.077*** (0.024)
Know Car Insurance	0.269*** (0.027)	—	0.268*** (0.027)	—	0.269*** (0.027)	—	0.269*** (0.027)	—
Know Savings and Debts	—	0.020* (0.012)	—	0.023** (0.012)	—	0.027** (0.012)	—	0.023** (0.012)
Financial Liquidity	0.528*** (0.136)	0.234*** (0.035)	0.536*** (0.137)	0.234*** (0.035)	0.556*** (0.136)	0.247*** (0.036)	0.540*** (0.136)	0.238*** (0.035)
Risk Tolerance	-0.089*** (0.025)	0.041*** (0.006)	-0.082*** (0.025)	0.043*** (0.006)	-0.081*** (0.025)	0.045*** (0.006)	-0.084*** (0.025)	0.043*** (0.006)
Constant	1.790*** (0.287)	-0.488*** (0.066)	1.723*** (0.287)	-0.518*** (0.065)	1.632*** (0.286)	-0.586*** (0.066)	1.703*** (0.286)	-0.532*** (0.065)
Correlation (ρ_{IR})	0.073** (0.028)		0.078** (0.028)		0.079** (0.028)		0.078** (0.028)	
Observations	1806		1806		1806		1806	
AIC	8248.0		8258.944		8304.645		8262.336	
1st Stage F-Statistic	__		206.34		130.45		187.20	

Model 1 : Baseline Model with wealth instrumented by median house price growth over the past 3 years within the respondent's zip code. **Model 2** : Baseline Model with Wealth instrumented by unexpected change in respondent's wealth over the past 12 months. **Model 3**: Wealth instrumented by previous 2 instruments. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Baseline Model with Interactions

	Baseline Model		Model 1		Model 2	
	$I_{i,1}$	R_i	$I_{i,1}$	R_i	$I_{i,1}$	R_i
Wealth ($100k)	0.435*** (0.058)	0.168*** (0.018)	0.536*** (0.081)	0.168*** (0.018)	0.448*** (0.081)	0.168*** (0.018)
Insurance Premium	0.020 (0.013)	—	0.020 (0.012)	—	0.020 (0.013)	—
Car Value	0.016*** (0.004)	—	0.018*** (0.004)	—	0.016*** (0.004)	—
Objective Risk Auto	0.050 (0.058)	—	0.054 (0.058)	—	0.063 (0.065)	—
Zip Density	-0.310 (8.248)	-0.525 (1.121)	-0.382 (8.205)	-0.525 (1.121)	-0.336 (8.246)	-0.525 (1.121)
Age	0.010*** (0.003)	-0.002** (0.001)	0.010*** (0.003)	-0.002** (0.001)	0.010*** (0.003)	-0.002** (0.001)
Gender	0.058 (0.083)	-0.011 (0.020)	0.063 (0.083)	-0.011 (0.020)	0.059 (0.083)	-0.011 (0.020)
Married	-0.038 (0.088)	0.052** (0.021)	-0.036 (0.088)	0.052** (0.021)	-0.039 (0.088)	0.052** (0.021)
Have Kids	0.109 (0.081)	0.022 (0.020)	0.102 (0.081)	0.022 (0.020)	0.108 (0.082)	0.022 (0.020)
Black	0.007 (0.150)	-0.029 (0.039)	0.006 (0.150)	-0.029 (0.039)	0.005 (0.150)	-0.029 (0.039)
Latino	-0.218 (0.159)	-0.014 (0.037)	-0.220 (0.159)	-0.014 (0.037)	-0.218 (0.159)	-0.014 (0.037)
Unemployed	-0.246 (0.287)	-0.067 (0.060)	-0.244 (0.286)	-0.067 (0.060)	-0.246 (0.287)	-0.067 (0.060)
High Education	0.182** (0.088)	0.070*** (0.021)	0.181** (0.088)	0.070*** (0.021)	0.183** (0.088)	0.070*** (0.021)
Low Education	-0.308*** (0.096)	-0.073*** (0.023)	-0.301*** (0.096)	-0.073*** (0.023)	-0.305*** (0.097)	-0.073*** (0.023)
Credit Score	0.018 (0.032)	0.033*** (0.008)	0.016 (0.032)	0.033*** (0.008)	0.017 (0.032)	0.033*** (0.008)
Subjective Risk Auto	0.167*** (0.047)	0.303** (0.127)	0.164*** (0.047)	0.303** (0.127)	0.163*** (0.054)	0.303*** (0.127)
Subjective Risk Stock	—	-0.076*** (0.024)	—	-0.076*** (0.024)	—	-0.076*** (0.024)
Low Financial Literacy	-0.243** (0.097)	—	-0.242** (0.098)	—	-0.244** (0.097)	—
Know Car Insurance	0.269*** (0.027)	—	0.269*** (0.027)	0.020* (0.012)	0.269*** (0.027)	0.020* (0.012)
Know Savings and Debts	—	0.020* (0.012)	—	0.020* (0.012)	—	0.020* (0.012)
Financial Liquidity	0.528*** (0.136)	0.234*** (0.035)	0.526*** (0.136)	0.234*** (0.035)	0.526*** (0.136)	0.234*** (0.035)
Risk Tolerance	-0.089*** (0.025)	0.041*** (0.006)	-0.089*** (0.025)	0.041*** (0.006)	-0.089*** (0.025)	0.041*** (0.006)
Car Value * Wealth	—	—	-0.006 (0.004)	—	—	—
Objective Risk Auto * Wealth	—	—	—	—	-0.038 (0.060)	—
Subjective Risk Auto *Wealth	—	—	—	—	0.012 (0.069)	—
Constant	1.790*** (0.287)	-0.488*** (0.066)	1.773*** (0.286)	-0.488*** (0.066)	1.793*** (0.289)	-0.488*** (0.066)
Correlation (ρ_{IR})	0.073** (0.028)		0.071** (0.028)		0.073** (0.028)	
Observations	1806		1806		1806	
AIC	8248.0		8247.0		8251.8	

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table X5 Homeowner and Renter Insurance

Wealth = Liquid wealth, $I_{i,1}$ = Simple index of coverage, R_i = Share of risky liquid assets

	Model with Homeowners		Model with Homeowners & Renters	
	$I_{i,1}$	R_i	$I_{i,1}$	R_i
Wealth ($100k)	0.310*** (0.076)	0.168*** (0.018)	0.291*** (0.074)	0.167*** (0.018)
Insurance Premium	0.098 (0.0081)	—	0.039** (0.018)	—
Replacement Cost ($100k)	0.852** (0.325)	—	1.305*** (0.353)	—
Objective Risk Auto	0.064 (0.062)	—	0.056 (0.057)	—
Zip Density	9.005 (6.436)	-0.544 (1.123)	1.749 (5.147)	-0.552 (1.124)
Age	0.009*** (0.002)	-0.002** (0.001)	0.007*** (0.002)	-0.002** (0.001)
Gender	-0.029 (0.068)	-0.012 (0.020)	-0.022 (0.058)	-0.012 (0.020)
Married	-0.064 (0.078)	0.052** (0.021)	0.009 (0.065)	0.052** (0.021)
Have Kids	0.072 (0.078)	0.022 (0.020)	0.099** (0.050)	0.022 (0.020)
Black	-0.043 (0.131)	-0.029 (0.039)	-0.057 (0.099)	-0.029 (0.039)
Latino	-0.204* (0.120)	-0.014 (0.036)	-0.014 (0.111)	-0.014 (0.036)
Unemployed	-0.453** (0.213)	-0.067 (0.060)	-0.030 (0.213)	-0.067 (0.060)
High Education	0.140 (0.092)	0.070*** (0.021)	0.210** (0.071)	0.070*** (0.021)
Low Education	-0.150* (0.080)	-0.073*** (0.023)	-0.149** (0.066)	-0.073*** (0.023)
Credit Score	0.005 (0.026)	0.033*** (0.008)	0.048** (0.021)	0.033*** (0.008)
Subjective Risk Home	0.254*** (0.043)	—	0.411*** (0.037)	—
Subjective Risk Stock	—	0.308** (0.126)	—	0.306** (0.126)
Low Financial Literacy	-0.177** (0.078)	-0.075*** (0.024)	-0.185*** (0.065)	-0.075*** (0.024)
Know Homeowner Insurance	0.123*** (0.024)	—	0.243*** (0.019)	—
Know Savings and Debts	—	0.020* (0.012)	—	0.021* (0.012)
Financial Liquidity	0.265** (0.120)	0.234*** (0.035)	0.415*** (0.092)	0.234*** (0.035)
Risk Tolerance	-0.063*** (0.021)	0.041*** (0.006)	-0.074*** (0.018)	0.041*** (0.006)
Constant	1.786*** (0.236)	-0.487*** (0.065)	0.154 (0.179)	-0.489*** (0.065)
Correlation (ρ_{IR})	0.070** (0.030)		0.068** (0.025)	
Observations	1,229		1,806	
AIC	5,502.2		7,369.5	

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Distributions of Wealth and Share of Risky Assets

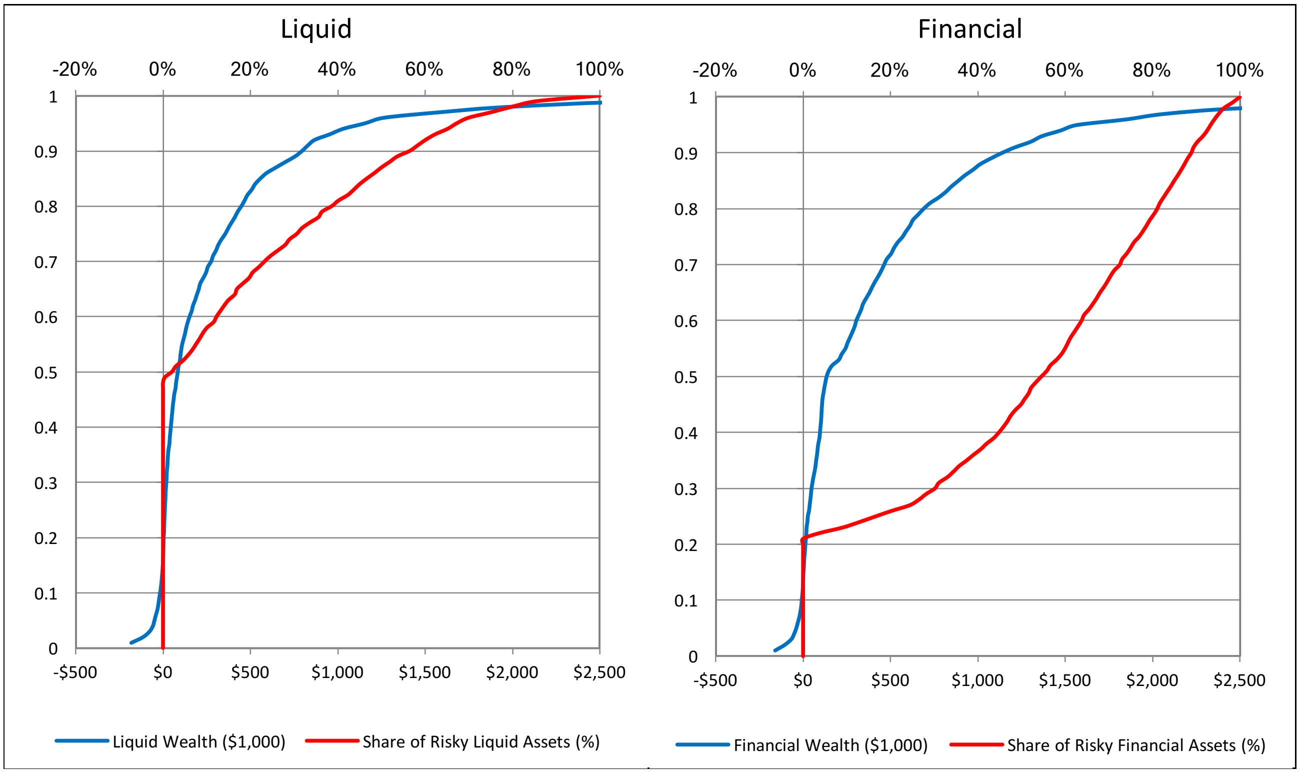
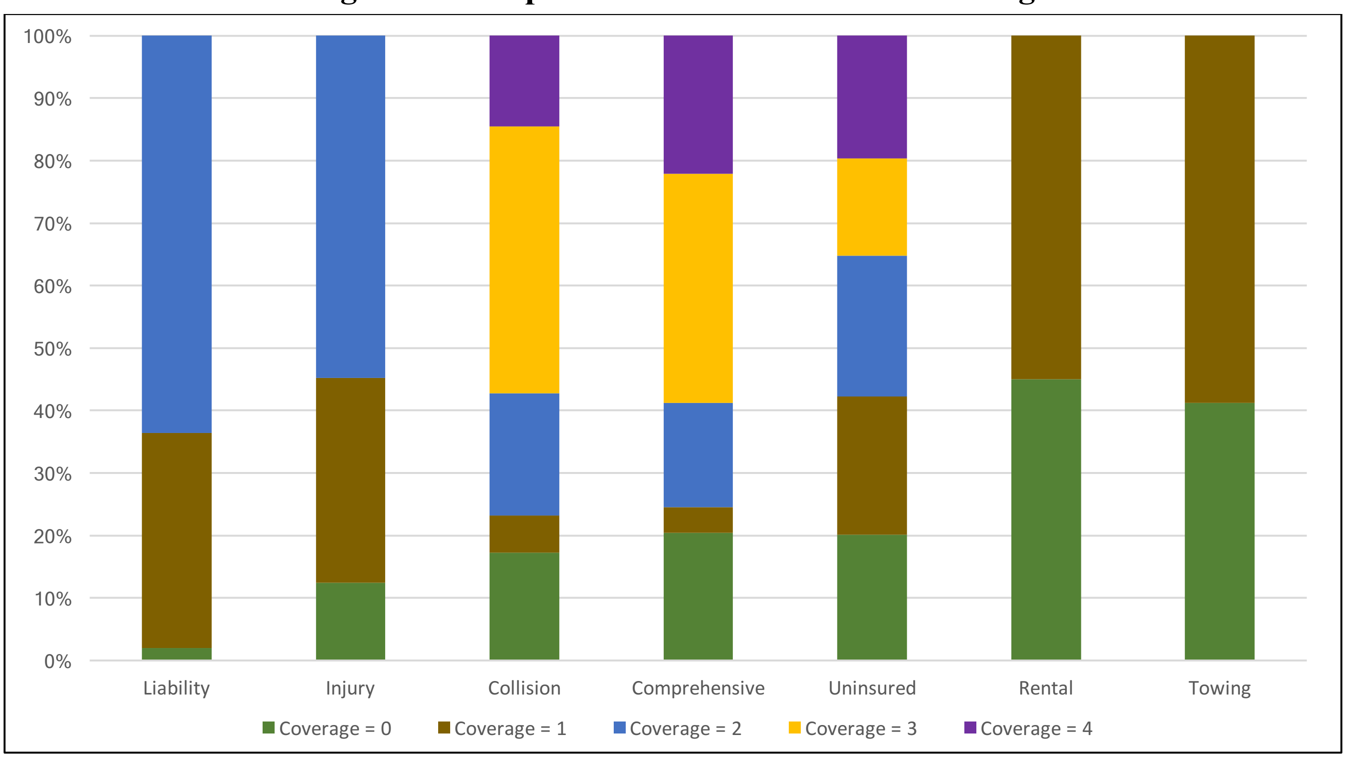
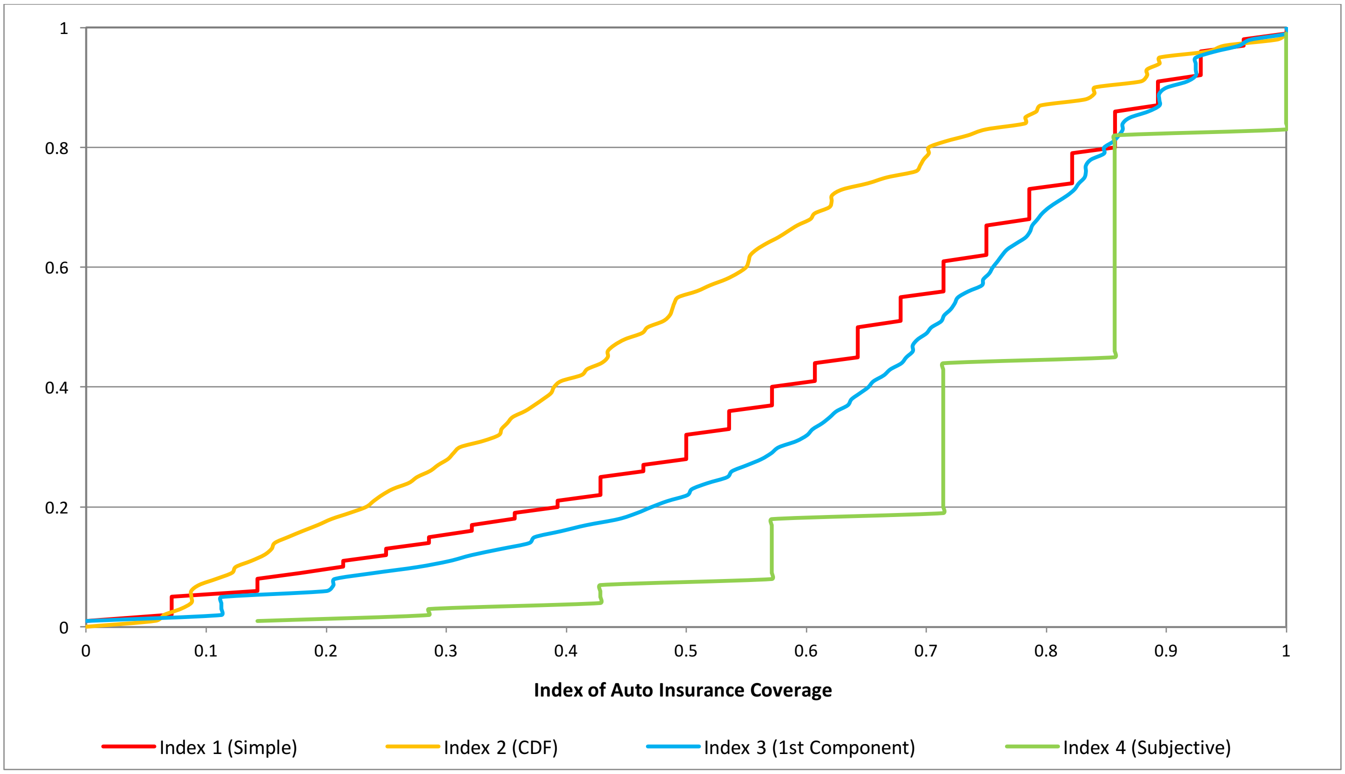


Figure 2: Components of Car Insurance Coverage



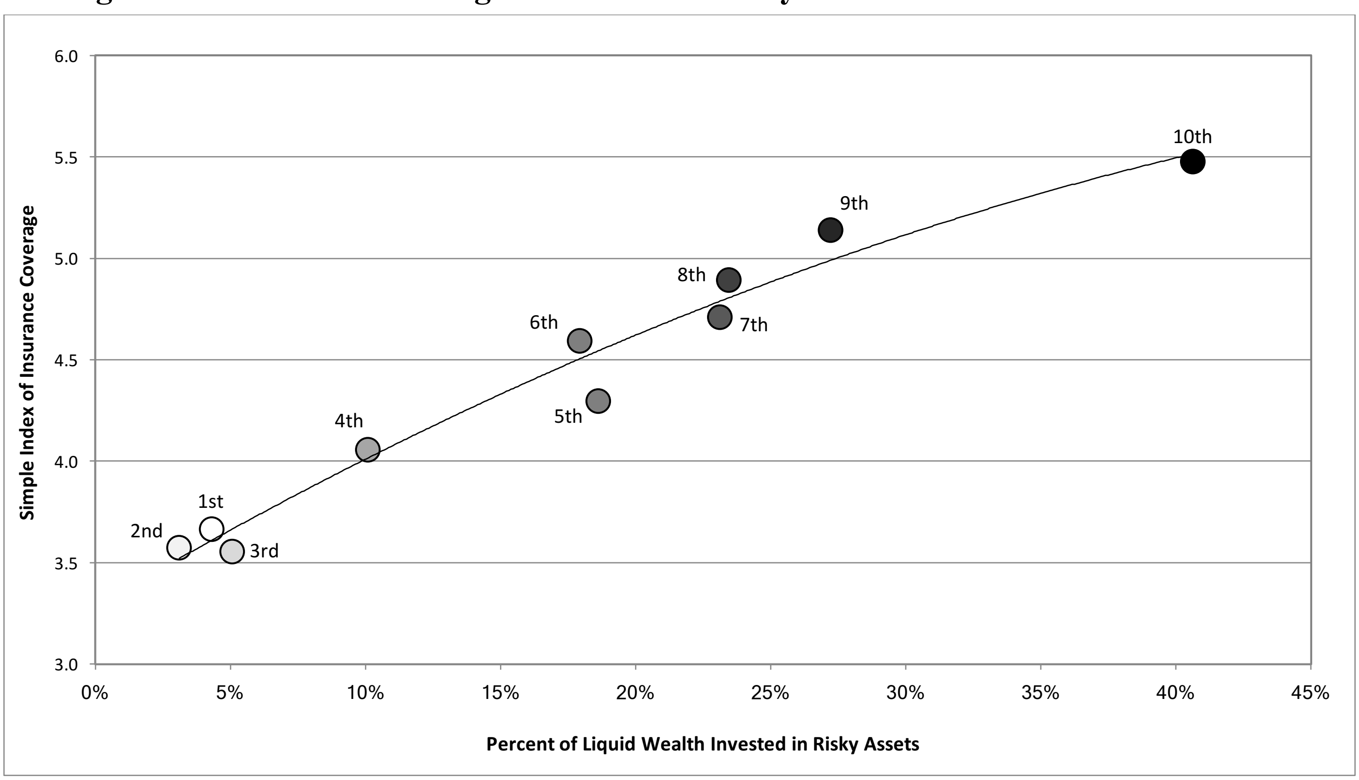
Liability: 0=No coverage, 1=Legal minimum, 2=More than legal minimum.
Injury: 0=No coverage, 1=Legal minimum, 2=More than legal minimum.
Collision: 0=No coverage, 1=deductible>$1,000, 2=$501<deductible<$1,000, 3=$251<deductible <=$500, 4=deductible<=$250.
Comprehensive: 0=No coverage, 1=deductible>$1,000, 2=$501<deductible<$1,000, 3=$251<deductible <=$500, 4=deductible<$250.
Uninsured: 0=No coverage, 1= Coverage<$10k, 2=$10k<coverage<$50k, 3=$50k<coverage<$100k, 4=Coverage>$100k.
Rental: 0=No coverage, 1=Coverage.
Towing: 0=No coverage, 1=Coverage.

Figure 3: Distributions of the Four Indexes of Auto Insurance Coverage



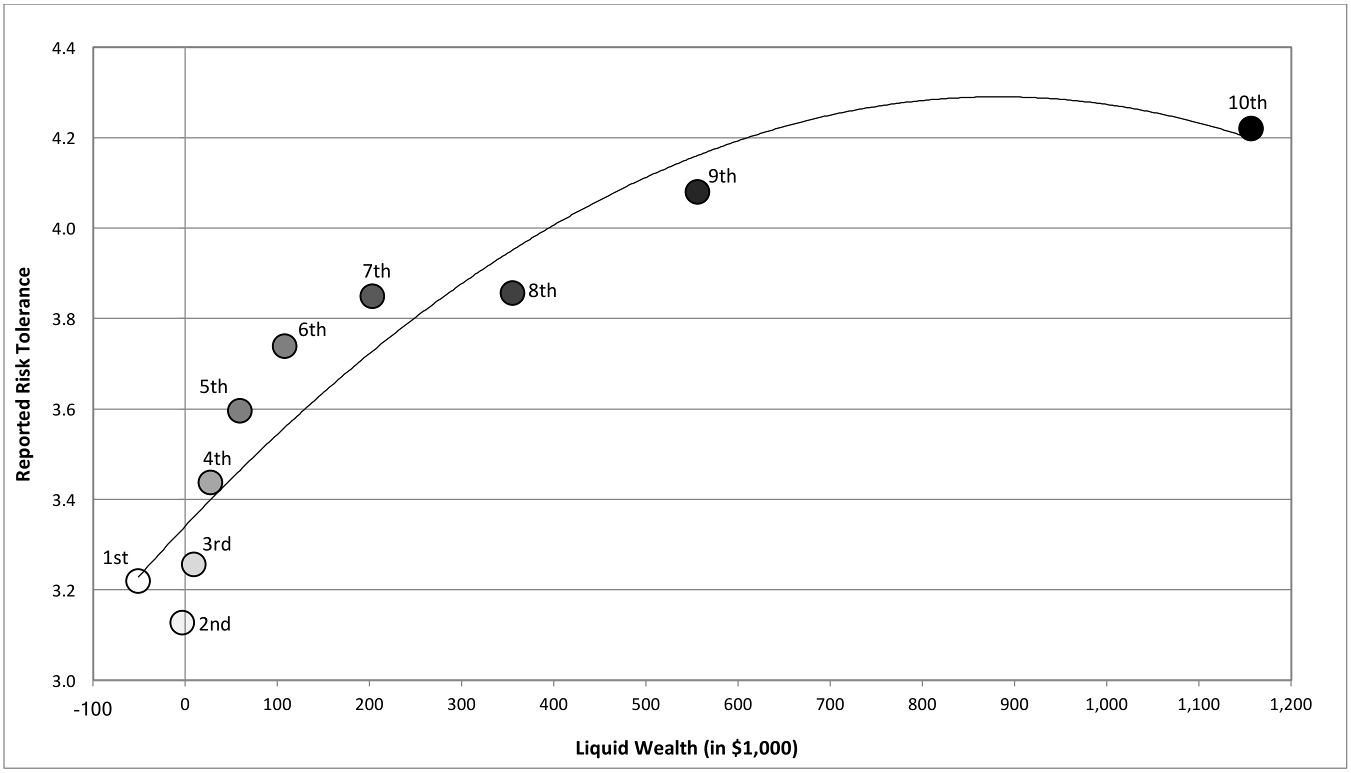
Each index has been normalized to 1 for comparison.

Figure 4: Insurance Coverage and Share of Risky Assets for Each Decile Wealth



Each dot corresponds a decile of liquid wealth.

Figure 5: Link between Wealth and Risk Tolerance by Decile of Wealth



Each dot corresponds a decile of liquid wealth.

Figure 6: Marginal Effects