Insurance and Portfolio Decisions: A Wealth Effect Puzzle

Olivier Armantier Jérôme Foncel Nicolas Treich*

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Abstract

We study empirically households' portfolio and insurance decisions, two opposite risk retention tradeoffs. We identify common determinants (e.g. subjective expectations, risk attitude) and frictions (e.g. liquidity constraints, financial literacy). We also find that risky investments and insurance coverage both increase with wealth, making insurance a normal good. This result appears to be a puzzle as we fail to explain it convincingly with standard and behavioral theory. Empirical evidence suggests that the puzzle is robust, economically relevant, and driven in part by "mistakes": the poor tend to invest too conservatively, while the rich tend to over-insure.

Keywords: Insurance demand, portfolio decisions, risk preferences, wealth, mistakes.

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*Olivier Armantier: Federal Reserve Bank of New York, USA, olivier.armantier@ny.frb.org. Jérôme Foncel: University of Lille 3, France. Nicolas Treich: Toulouse School of Economics (TSE), INRA, University Toulouse Capitole, France.
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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. In particular, because the wealth elasticity of demand for risky assets has been shown to be positive,[1] insurance coverage should decrease with wealth, making insurance an inferior good. The object of this paper is to explore the link between portfolio and insurance decisions, and in particular to test the hypothesis that wealth has an opposite effect on the two decisions.

To do so, we use survey data for a representative sample of U.S. household heads which combines detailed micro 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 focusing on auto insurance coverage and investment 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 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 theory. We also identify several frictions, including liquidity constraints, financial literacy,

[1] See e.g. Friend and Blume (1975), Guiso, Jappelli and Terlizzese (1996), Carroll (2002), Campbell (2006), Wachter and Yogo (2010), Calvet and Sodini (2014), or Fagereng, Guiso and Pistaferri (2018). 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 suggest that insurance may be a normal good (see e.g. Guiso and Japelli 1998 or Millo 2016 for a review). These analyses, however, suffer from limitations, e.g. they rely on aggregate data or they do not control for key determinants such as the value of the good insured or the risks faced by the insured (both of which are likely to be correlated with wealth).

or information, that impede both the demand for risky assets and the demand for insurance.

To explain the insurance-portfolio puzzle, we first turn to conventional theory. We show that our results are not consistent with the canonical portfolio/insurance model (Pratt 1964, Mossin 1968). We then enrich the model by considering in particular the possibility that insurance and investment decisions are taken jointly, that losses depend on wealth, or that the agents are liquidity constrained. Next, we explore various behavioral factors including prospect theory, context-dependent preferences, and "peace of mind." We conclude that conventional and behavioral theories are insufficient to explain the puzzle fully.

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 households' 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 mostly focussed on testing for the presence of asymmetric information in insurance markets,[4] and 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 same coin.

The paper is structured as follows. The econometric approach and the data are presented in Section 2. Descriptive statistics and prima-facie evidence of the insurance-portfolio puzzle are provided in Section 3. Estimation results for the baseline mode are discussed in Section 4. Robustness checks are conducted in Section 5. We gauge the economic significance of the puzzle in Section 6. We show in Section 7 that it is difficult to explain the insurance-portfolio puzzle with standard and behavioral theory. Finally, we conclude in Section 8.

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, Haliassos and Jappelli (2002), Campbell (2006), Guiso and Sodini (2013), or Badarinza, Campbell and Ramadorai (2016) for reviews.
[4] See Cohen and Siegelman (2010), Einav, Finkelstein and Levin (2010), or Chiappori and Salanié (2015).
[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.

One of the main exercises of the paper is to test joint hypotheses such as: $H_0 = \{\alpha_0 < 0, \beta_0 > 0\}$, i.e. that wealth has an opposite effect on portfolio and insurance decisions. Thus, we are concerned primarily with identifying the signs of the parameters. Although the model in (1) is certainly not immune to possible biases, we conduct various robustness tests showing that it is adequate to test our hypotheses.

2.2 The Data

The baseline model is estimated with data collected in the Survey of Consumer Expectations (SCE), focusing on households' 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 objective 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. Data from the SCE have been used to address both policy and research questions.[6]

The data on wealth composition and portfolio allocation come from two special surveys on household finance conducted in August 2015 and August 2016 with different sets of respondents. In addition, we fielded two special modules on insurance (focusing on car, homeowner, and health insurance), one in September 2015, the other in September 2016.[7]

[6] See e.g. Armantier et al. (2015, 2016b) or Armona, Fuster and Zafar (2018).

[7] We focus in the paper on car and homeowner insurance because, unlike e.g. life or health insurance, they entail mostly financial losses and are thus more directly comparable to investment decisions.

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.[8]

The SCE is quantitative in nature and, prior to taking our surveys, respondents had experienced answering cognitively demanding questions involving dollar amounts, rates and percentages. The household finance survey asks for detailed information about savings, investments and debts. The insurance survey asks about specific features of the respondent's insurance contracts, including coverage, deductibles, and premiums.[9] 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's 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's 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.[10] 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

[8] In principle, panel data are preferable to control for unobserved individual characteristics. The use of panel data in our context, however, is not without challenges. In particular, the duration of the panel should be long enough to observe meaningful changes in wealth, but sufficiently short to guarantee that unobserved individual characteristics remain unchanged. Note also that we control for several variables often considered unobserved (e.g. risk attitude, financial literacy, liquidity constraints) which should alleviate some of the usual concerns with using cross sectional data.

[9] The questions asked in the household finance and insurance surveys are available upon request.

[10] 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.

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 and towing 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.

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 et al. (2011, 2018) restrict the analysis to the choice of deductibles for collision and comprehensive coverage.[11] 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 owner 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 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").[12]

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 in Section 3, there is a strong correlation between the four indexes. Further, unlike any single component of the vector of insurance

[11] 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.

[12] $I_{i,4}$ was measured only in the 2016 survey.

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 related 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 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) 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.[13]

Insurance and investments specific covariates (Y_i and Z_i). The variables relevant to a respondent's insurance decision consist of the value of the respondent's main vehicle (i.e. how

[13] As discussed in Section 7, theoretical analyses of the effect of wealth on investments consider usually the amount invested in risky assets, not the share. Nevertheless, we follow the empirical literature and study the share in the baseline model. Obviously, if wealth increases the share, it must also increase the amount.

much the respondent thinks it would sell for on today's market), the annual premium paid by the respondent to insure this main vehicle,[14] the population density in the respondent's zip code (a variable typically considered a proxy for vehicle risk exposure), a measure of the respondent's objective risks (based on the respondent's 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 damages the respondent expect to incur over the next two years),[15] as well as a qualitative measure of the respondent knowledge of his car insurance contract.[16]

The variables relevant 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's 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 and Mitchell 2007),[17] 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).[18]

[14] Unlike e.g. Sydnor (2010), we only observe the total premium paid, not the premium paid for each component of the contract. Further, note that the premium is not a price per unit of insurance, it is the total expense on insurance.

[15] 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 and 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.

[16] As discussed by e.g. Chiappori and Salanié (2000) or Cohen and Siegelman (2010), a common issue with previous studies of insurance is that damages are only observed if they lead to the submission of a claim. This is potentially a problem since the probability to submit a claim likely depends on coverage (e.g. drivers with high deductibles should submit fewer claims). We do not face this problem here since our measures of risks capture all damages including those for which the respondent does not submit a claim.

[17] 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?*".

[18] 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.

3 Descriptive Statistics and Prima-Facie Evidence

Descriptive statistics are reported in Tables 1 to 6 and Figures 1 to 5. Overall, the data collected on wealth composition, portfolio allocation and insurance coverage appear 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 and 39% of households have children currently living in the primary home. The median respondent 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. Consistent with the analysis conducted by Armantier et al. (2017), respondents are essentially representative of the U.S. population of household heads with respect to gender, race, income, geography, and age, but they are slightly more educated than in the 2010 census.[19]

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% (respectively 13%) of the respondents report having negative liquid (respectively financial) wealth, meaning that their total debt exceeds the current market value of their assets.[20] 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 (respectively median) home equity (conditional on owning a home) is $199k (respectively $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).[21]

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

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

[21] Unlike Brunnermeier and Nagel (2008), we do not exclude households with wealth below $10k. Doing so would reduce our sample by roughly 20%. Further, excluding the poorest households does not seem

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.[22] The proportion of respondents who report having incurred 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.[23] 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, 2018). While the majority (80%) of respondents report having uninsured insurance, coverage is 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 show 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.[24]

We conclude this section by providing prima-facie evidence of the link between wealth, auto insurance coverage and risky investments. In Figure 4, we plot the average share of risky

appropriate since we want to study the effect of wealth on insurance and portfolio decisions.

[22] These figures are in line with the University of Michigan's *Transportation Research Institute,* as well as estimates from *Edmunds* for the same time period.

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

[24] 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.

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 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) while controlling for relevant explanatory variables.

4 Estimation Results from the Baseline Model

We report in Table 7 the estimation results for the baseline regression model. Recall that the baseline model is specified in equation (1) with the dependent variables being the index of auto insurance coverage $I_{i,1}$ and the share of risky liquid assets, while the main 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 7) 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 should not be modeled 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.[25]

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

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

Models 2 and 3: Characteristics of insurance contracts. We augment the specification in Models 2 and 3 of Table 7 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.[26]

Model 4: Standard socio-demographic characteristics. In Model 4 of Table 7 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 indicate 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.[27] 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.[28]

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 controls. Finally, we fail to identify a significant effect of employment status, race, and family composition (i.e. whether or not the household includes children).[29]

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

[27] The second result is consistent with (e.g.) Fagereng, Gottlieb 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.

[28] The positive effect of education on risky portfolio allocation is consistent with (e.g.) Campbell (2006), or Guiso et al. (2002).

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

Model 5: Behavioral factors and frictions. We augment the specification in Model 5 of Table 7 by adding controls for subjective risks, financial literacy, information and liquidity constraints. These behavioral factors and frictions all seem to have strong explanatory power. In particular, we find 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 Arrondel, Calvo-Pardo and Tas 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.[30]

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 (2018) find that information and attention are positively related to 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).[31] 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.[32]

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 invest more conservatively. Similarly, Fang, Keane and Silverman (2008) find that elderly people with lower cognitive abilities are less likely to purchase Medigap insurance,

[30] 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.

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

[32] The correlation between wealth and the measure of financial liquidity (0.22) is positive but not perfect in our data. This reflects the well documented fact that some households although wealthy can be cash strapped (see Lusardi, Schneider and Tufano 2011, or Lusardi, Mitchell and Oggero 2018).

while van Rooij, Lusardi and Alessie (2011) and Lusardi, Michaud and Mitchell (2017) 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 (2017) 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 7. Before we discuss the estimation results, we make two brief comments. First, in theory wealth affects investment and insurance decisions only through the Arrow-Pratt coefficient of absolute risk aversion $A(.)$ (see Section 7). 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. 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 decreasing absolute risk aversion (DARA). As discussed in Section 7, this finding is consistent with numerous empirical and experimental analyses and it provides support for the standard portfolio and insurance models which assume DARA.

Turning to the estimation results in the last column of Table 7, 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.[33] 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 equations. 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 standard utility function channel, a possibility we discuss in Section 7. More generally, our results suggest that the effect of wealth on insurance and investment decisions is not purely a risk preference shifter. Indeed, we find that wealthier respondents are more risk seeking (Figure 5), but nevertheless they tend to purchase more insurance coverage.

We conclude with a short discussion of fit. To appreciate how well the model fits the

[33] 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.

data, we plot in Figure 6 the actual (black line) and predicted (red line) values of the risky liquid share (left panel) and the insurance index (right panel) for each decile of wealth (the other explanatory variables are taken at the median). Overall, the predicted values track the data well thereby suggesting that our baseline model provides a reasonable fit to the data.

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 7.

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 A1 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.[34]

A potential issue with the insurance indexes considered so far is that the legal requirements for auto insurance differ from state to state. 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 states with similar legal requirements. These requirements are summarized in the form *"a/b/c"* where *a, b* and *c* 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.[35] In 2016, the legal requirements varied from 10/20/10 in Florida to 50/100/25 in Maine and Alaska. In Table A1, 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 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 A1, the new index $I_{i,1}^{-}$ is now a combination of only the collision, comprehensive, underinsured, rental and towing components.

As can be observed in Table A1, virtually all the results discussed in the previous section still hold under these alternative specifications. Notably, the wealth parameters remain

[34] Tables and Figures with numbers preceded with an "A" can be found in Appendix A.
[35] Some states also have secondary requirements for (e.g.) medical payments or personal injury.

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 A2, 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 uses the financial wealth and the amount invested in risky financial assets. Again, we can see in Table A2 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 A3, 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 the significance, of the estimated parameters differ slightly compared to the baseline model (as may be expected due to smaller sample sizes), 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 A4. Model 1 accounts for the log of wealth,[36] 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 the median of wealth). Four points are worth noting in Table A4. 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. 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 A4). Fourth, as can be seen in Figure 6, 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 A4 that the

[36] 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.

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 seems 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 A5 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 2008) and the second measures the respondent's 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 A5 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.[37]

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 of wealth, we add in Table A6 interaction effects in the insurance coverage equation. The results reported in Table A6 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.[38]

[37] 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, and 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.

[38] We also estimated a model with an interaction effect between wealth and reported risk attitude. The interaction effect was not significant and the other parameters were essentially unaffected.

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 respondent 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), 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 A7. 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 Sydnor 2010).[39] 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).[40]

We report in Table A8 the estimates of the model with home insurance. Model 1 includes homeowners only, while Model 2 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 (e.g. age, education, beliefs). Further, the wealth parameters are positive and significant in all equations in Table A8 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.

[39] 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.
[40] 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, while most respondents with umbrella insurance are in the third quartile of wealth.

Firm data from France. We conclude by testing the insurance-portfolio puzzle with data from a French company (Credit Agricole) that offers both car insurance and traditional banking services. This robustness test is interesting for two reasons. First, it relies on firm data rather than self-reported survey data.[41] Second, there are major institutional differences between the French and U.S. insurance systems. Most notably, there is no limit on insurance coverage in France.[42]

The sample consists of 24,642 observations, each corresponding to an individual with a bank account and a car insurance contract at Credit Agricole in 1999. To the extent possible, we define the variables as in the baseline model. Liquid wealth consists of all the money held by the individual at Credit Agricole on checking, savings and investment accounts.[43] Risky assets are measured by the share of liquid wealth invested at the bank in stocks, bonds and risky financial instruments.

As explained by Chiappori and Salanié (2000), there are essentially two insurance contracts in France: "Au Tiers," a compulsory liability contract, and "Tous Risques," a full coverage contract which also covers the damages the insured is responsible for.[44] In addition, we observe the annual premium paid and a measure of objective risk, the "Bonus-Malus" (see Chiappori and Salanié 2000). Although we do not observe the current value of the car it can be proxied by the vehicle's age and the manufacturer recommended price when the vehicle was purchased new.

Finally, demographic variables are limited to gender, age, employment status, population density and a measure of credit worthiness.[45] The French data appear sensible. In particular, stock participation (20.6%) is in line with the estimates by Guiso, Haliassos and Jappelli (2003) for France, while roughly two out of three drivers purchased a "Tous Risques" contract, consistent with Dionne, Michaud and Dahchour (2013).

The model is estimated for the baseline specification in (1), but the insurance equation is now a Probit since I_i is a binary variable. The results reported in Table A9 indicate that portfolio and insurance decisions are driven by similar determinants in France and in the U.S.

[41] Firm and survey data each have advantages and drawbacks. While firm data are less likely to suffer from measurement errors and biases, survey data are often more comprehensive (e.g. providing detailed information about wealth composition and demographics) and more representative.

[42] See e.g. www.index-assurance.fr/pratique/devis-souscription/garanties/la-responsabilite-civile.

[43] In contrast with the U.S. data, we do not have a comprehensive measure of wealth. In particular, we do not observe non-banking wealth, assets held at other banking institutions, and (non-housing) debt (e.g. loans, credit cards, medical or legal bills). Note, however, that credit cards, medical and legal bills are not common France, while holding accounts at different banks was rare in France at the time (Daley 2005).

[44] "Tous Risques" contracts have deductibles. As explained in Chiappori and Salanié (2000), these deductibles are small and can be ignored.

[45] "Credit worthy" is a dummy variable equal to 1 unless the individual had a payment incident with Credit Agricole or has been forbidden by law to hold a checkbook.

(e.g objective risk, credit worthiness). There are however some differences between the two countries (e.g. men and older people appear to invest more aggressively in France). These differences, however, likely reflect the facts that i) the regression in Table A9 lacks controls (e.g. for education and risk attitude) and ii) the retirement systems differ substantially in each country. More importantly, we can see in Table A9 that the parameter associated with wealth is positive and significant in both the insurance and risky investment equations. Thus, we find evidence that the insurance-portfolio puzzle is not confined to the U.S. and applies as well in a country in which liability coverage is not bounded.

6 Economic Magnitude of the Puzzle

We have just established that the insurance-portfolio puzzle is statistically significant and robust. In this section we try to gauge the economic significance of the puzzle. The exercises we conduct, however, are more back-of-the-envelope calculations than formal estimates.

Relative magnitude. We start by evaluating the impact of a wealth shock on insurance coverage and risky investments. Using the estimates from the baseline model (Model 6 in Table 7), we find that if an individual were to move from the first to the third quartile of liquid wealth, then all else equal (i.e. taking all the other explanatory variables at their median), the share the individual invests in risky assets would increase from 8.1% to 23.2% (an increase of 0.64 standard deviation or 14.4 percentile points), while his index of car insurance coverage would increase from 3.8 to 4.8 (an increase of 0.58 standard deviation or 22.2 percentile points).

To put these numbers in perspective, we conduct the same exercise with risk tolerance: All else equal, an individual moving from the first to the third quartile of risk tolerance would increase the share he invests in risky assets from 10.7% to 20.5% (an increase of 0.42 standard deviation or 9.5 percentile points), while his index of insurance coverage would decrease from 4.7 to 4.0 (a decrease of 0.42 standard deviation or 16.6 percentile points). In other words, the effect of a 50 percentile points shift in the wealth distribution on risky investments and insurance coverage is roughly 1.5 times larger than the effect of a 50 percentile points shift in the risk tolerance distribution.[46]

[46] We also compared an "optimist" (located at the first quartile of expected car damages and the third quartile of expected changes in the U.S. stock market) to an otherwise identical "pessimist" (located at the third quartile of expected car damages and the first quartile of expected changes in the U.S. stock market). The shift from pessimism to optimism increases the share invested in risky assets from 11.6% to 19.5% (an increase of 0.34 standard deviation or 7.8 percentile points), while it decreases the index of insurance coverage from 4.6 to 4.1 (a decrease of 0.32 standard deviation or 12.0 percentile points). Thus, the effect of a 50 percentile points shift in the wealth distribution on risky investment and insurance coverage is substantially larger than a 50 percentile points shift in subjective beliefs.

Cost of the puzzle. Next, we rely on theory to assign a monetary value to the puzzle. To do so, we assume that the respondents in our sample are expected utility maximizers and exhibit DARA.[47] In that case, we will see in Section 7 that the positive relationship we identified empirically between wealth and risky investments is consistent with theory, whereas the positive effect of wealth on insurance coverage cannot be rationalized and thus reflects decision "mistakes." These mistakes could be due to the wealthy who over-insure or to the poor who under-insure. At this point, we do not take a stance on who make mistakes. Instead, we simply gauge the cost of possible insurance mistakes separately for the poor and for the wealthy. To do so, we consider two representative agents, which we call "Poor" and "Wealthy" to simplify, by taking the median of each variable across respondents located in the first and fourth quartiles of wealth, respectively. For instance, Wealthy and Poor have a car worth $15.0k and $6.5k, respectively.

Let us first gauge the cost of over-insuring for Wealthy. If Wealthy had been located in the first quartile of wealth (instead of the fourth), then our model predicts that, all else equal, Wealthy's insurance coverage would have been 4.3. Thus, Wealthy over-insured by at least 1.1 index points. Indeed, he selected an index of insurance coverage of 5.4 when he should have selected an index no greater than 4.3 (because insurance coverage decreases with wealth under DARA). As reported in Table A10, we estimate an auxiliary insurance premium model to evaluate how much Wealthy would have saved by selecting the lower insurance premium. We find that Wealthy's premium should have been no greater than $817 instead $900. In other words, by over-insuring Wealthy increased his premium payment by at least 9.2%. When we conduct the same exercise for Poor, we find that he should have selected an index of insurance coverage no lower than 4.7 instead of 3.7, which would have increased his insurance premium by at least 12.0%, from $812 to $909.

Investment and insurance mistakes. Finally, we turn to the issue of possible investment and insurance "mistakes." Previous literature has established that the wealthy tend to make fewer investment mistakes. In particular, Calvet, Campbell and Sodini (2009) report that richer households are better diversified, display less portfolio inertia and are less exposed to the disposition effect. We consider three criteria in Figure 7: Stock market participation, portfolio diversification and equity exposure over the lifecycle. The left panel of Figure 7 shows that stock market participation increases monotonically with wealth. The central panel provides evidence that respondents' portfolio are more concentrated at the lower end of the wealth distribution.[48] Finally, the right panel shows that equity exposure among the

[47] Assuming DARA is standard in the theory literature on portfolio and insurance decisions (see Section 7). Further, the shape of reported risk tolerance in Figure 5 is consistent with DARA.

[48] We adopt a crude measure of portfolio concentration: In the SCE, respondents are asked to report the proportion of their assets in i) checking and savings accounts, ii) Treasury bills, certificates of deposits,

rich is more consistent with the optimal life-cycle asset allocation of Gomes and Michealides (2005).[49] In other words, consistent with previous literature, we find evidence supporting the hypothesis that the wealthy are less prone to investment mistakes and that the poor tend to under-invest in risky assets.

The literature on insurance "mistakes" (e.g. Rabin and Thaler 2001, Gollier 2003, Sydnor 2010) is thinner and, to the best of our knowledge, it has not established an explicit link between under/over-insurance and wealth. We consider in Figure 8 four common measures of "under-insurance."[50] The first panel shows the proportion of drivers in the sample with low auto liability coverage.[51] The next two panels show the proportion of homeowners with low home liability and dwelling coverage, respectively.[52] Finally, the last panel shows the proportion of renters in the sample without renter's insurance. Figure 8 reveals that under-insurance is a relatively prevalent problem, as often argued in the popular press. In particular, roughly half of homeowners have low home liability coverage, while 42% of renters are not insured.[53] Observe however, that no consistent pattern emerges between under-insurance and wealth.

We consider four measures of over-insurance in Figure 9. The first two panels show the

money market funds, money market mutual funds, iii) Treasury inflation protected securities (TIPS), and TIPS index funds, iv) bonds, bonds mutual funds (including U.S. government bonds, municipal bonds and corporate bonds), v) stocks and stock mutual funds, and vi) real estate investment trusts (REIT) and REIT index funds. Portfolio concentration is then measured by the Herfindal index of the respondent's portfolio.

[49] To make sure our results are not driven by stock market participation, we exclude respondents without risky assets in the right panel of Figure 7. Accounting for respondents without stock makes the difference between rich and poor even more pronounced. It should to be noted that there is no consensus in the literature on the shape of the optimal "glide path," that is on how equity exposure should evolve over the life cycle (see e.g. Estrada 2014). Here, we use the optimal equity exposure over the lifecycle calculated by Gomes and Michealides 2005 (page 883) as a benchmark. Note however, that the nature of our results does not change when we consider alternative glide paths (e.g. inverse U-shape), including popular rule of thumbs (e.g. "100 (or 120) minus your age in stock", or "your age in bonds").

[50] These measures are typically listed among the most common insurance mistakes by consumer advocates (see e.g. www.consumerreports.org/cro/2013/05/4-big-insurance-mistakes-to-avoid/index.htm)

[51] A respondent is said to have low auto liability insurance when three conditions are met: 1) the respondent purchased the minimum auto liability coverage required by law in his state, 2) this minimum is less than half of the respondent's assets exposed to liability suits (i.e. all the respondent's assets absent retirement savings which are exempt from creditors), and 3) the respondent does not have an umbrella insurance. This measure should be considered a lower bound. Indeed, drivers who purchased more than the legal minimum could still be under-insured. Note that the survey did not ask for the exact amount of liability coverage for auto insurance, which explains why we are not able to calculate a more precise measure.

[52] A homeowner is said to have low home liability insurance when his home liability coverage is less than half of his exposed assets and the homeowner does not have an umbrella insurance. A homeowner is said to have low dwelling insurance when his dwelling coverage is less than half of his replacement cost (the cost of rebuilding his home). Using benchmarks other than 50% produces similar results.

[53] According to *III,* 41% of renters did not have renters insurance in 2016. Note also that the inverse U-Shape in the first two panels of Figure 8 is not necessarily surprising. Indeed, the poorest and wealthiest respondents are less likely to under-insure on liability, because the former have few assets while the latter are more likely to have an umbrella insurance.

proportion of homeowners in the sample who purchase too much liability and dwelling coverage, respectively.[54] The last two panels focus on insurance add-ons typically considered unnecessary: roadside assistance and towing coverage for auto insurance and extended warranty for appliances and durable goods.[55] Each panel on Figure 9 displays the same pattern: Over-insurance is not rare and it is more prevalent among the wealthy.

To sum up, we find evidence suggesting that i) the effect of wealth on insurance and portfolio decisions is meaningful compared to other explanatory variables, ii) the poor tend to under-invest in risky assets, while the rich tend to over-insure, and iii) the cost of over-insuring for the rich is of the order of 10% of their insurance premium.

7 Possible Explanations for the Puzzle

7.1 Standard Theory

We propose several hypotheses based on standard theory to explain the insurance-portfolio puzzle.

Mossin-Pratt model. Pratt (1964) considers an expected utility model in which an agent can invest in a riskless and a risky asset. As is well known, this model is equivalent to the coinsurance model of Mossin (1968) (see Appendix B.1 for formal details). Moreover, the demand for risky assets increases with wealth iff DARA (Pratt 1964), while insurance demand increases with wealth iff IARA (Mossin 1968).[56] Consistent with experimental

[54] A homeowner is said to over-insure on home liability when his coverage exceeds by at least 25% his exposed assets. A homeowner is said to over-insure on dwelling when his coverage exceeds his replacement cost by at least 25%. Using benchmarks other than 25% produces similar results. Although positive, the correlation between these two variables is not large (0.110). Thus, it appears that the homeowners who over-insure on liability are not systematically the same as the homeowners who over-insure on dwelling.

[55] Consumer groups typically advise against purchasing add-ons auto insurance such as roadside assistance and towing because the coverage is often redundant (many new vehicles come with a 3 to 10 years roadside assistance plan and several credit cards offer roadside assistance as a benefit) and there are better alternatives (e.g. joining an automobile club). As defined by Abito and Salant (2018) "An extended warranty is an insurance contract that protects against the failure of a durable good such as a consumer electronic." Although almost universally described as a waste of money by consumer advocates, the willingness to pay for extended warranties is high. This failure to self-insure has been somewhat of a puzzle to economists. Recently, probability misperceptions (e.g. Abito and Salant 2018) and loss aversion (Jindal 2014) have been proposed to explain the puzzle. In the survey, we asked "*When purchasing new appliances (such as electronics or home appliances), how often do you also purchase an insurance or extended warranty? (1) Every time or almost every time (2) Sometimes (3) Never or almost never.*" The right panel in Figure 9 shows the proportion of respondents who selected (1) or (2). Finally, note that unlike (e.g.) Sydnor (2010), we do not have information about the deductible-premiun menu (i.e. the customer cost of reducing his deductible) for auto and home insurance. Hence, we cannot evaluate the extent to which respondents over-insure by selecting low deductibles.

[56] Mossin's result regarding the effect of wealth on insurance demand holds as well when the insurance decision is modeled as a deductible and not as coinsurance (Schlesinger 2013).

(e.g. Holt and Laury 2002), survey (e.g. Guiso and Paiella 2008), and field data (e.g. Brunnermeier and Nagel 2008), we find evidence supporting DARA, not IARA (see Figure 5). Moreover, because the standard expected utility model admits a single utility function, it cannot explain at the same time that insurance is a normal good consistent with IARA, and that the demand for risky assets increases with wealth consistent with DARA.

Simultaneous decisions. The Mossin-Pratt model assumes that the agent makes only one decision, either an insurance or an investment decision. We relax this assumption and study in Appendix B.2 a model in which insurance and portfolio decisions are made simultaneously.[57] Intuitively, if one takes more risk on one side (e.g. one demands more risky assets), then one may be willing to take less risk on the other side (e.g. one demands more insurance), in which case insurance and portfolio decisions would be complementary, not substitutes. To study this intuition, we use a "small risks" approximation. We first show that investments in risky assets act as an (endogenous) background risk and indeed raise insurance demand (see equation (6) in Appendix B.2). Nevertheless, we show that insurance demand decreases with wealth and that the demand for risky assets increases with wealth iff DARA. Hence, the standard opposite effect of wealth on insurance and portfolio decisions is preserved despite the fact that the two decisions are made simultaneously and not separately. Furthermore, we show in Appendix B.3 that this result is also preserved in a two-period model where a savings decision is made simultaneously with an insurance and/or portfolio decision, as in Aura, Diamond and Geanakoplos (2002).

Wealth-dependent loss/probability. The Mossin-Pratt model assumes that losses are independent of wealth. In practice, the wealthy are likely to have more expensive goods to insure, and thus face higher potential losses. We consider in Appendix B.4 a wealth-dependent loss. We show that insurance can be a normal good even under DARA when the wealth-elasticity of the good is high enough. Nevertheless, this effect should not explain the puzzle since the regressions controlled for the value of the good insured and possible interaction effects with wealth (see Table A6). Relatedly, the probability distribution of the loss may also depend on wealth. However, we controlled for this effect through the measures of respondents' subjective and objective risks and their possible interactions with wealth. Overall, it does not seem plausible that a wealth-dependent loss/probability can explain that insurance is a normal good.

[57] A few papers (Eeckhoudt, Meyer and Ormiston 1997, Meyer and Meyer 2004, Loubergé and Watt 2008) show, using a model involving simultaneous decisions, that insurance demand can increase with wealth for a subset of DARA agents.

Liability insurance. In practice, liability losses are bounded by wealth. As discussed in the previous paragraph and Appendix B.4, the general Mossin result that wealth decreases insurance demand iff DARA does not hold anymore when losses are wealth-dependent. However, as explained in Section 5, the effect of wealth on insurance demand remains positive and statistically significant when we consider an index of coverage that excludes liability coverage (see Model 6 of Table A1). Moreover, the French data provide additional evidence that the puzzle is not driven by wealth-dependent liability losses, since liability insurance in France is compulsory and unlimited regardless of wealth.

Liquidity constraints. The Mossin-Pratt model assumes that agents can always pay the insurance premium. However, this may not be the case in practice, and liquidity constraints could explain low insurance take up by the poor.[58] Consistent with this hypothesis, we found in Section 4 that respondents facing liquidity constraints demand less insurance. The insurance-portfolio puzzle, however, remained when we controlled for "financial liquidity" (Model 6 in Table 7). Further, the results in section 6 suggest that the puzzle is driven more by the wealthy who over-insure than by the poor who under-insure. We therefore conclude that the insurance-portfolio puzzle is unlikely due to liquidity constraints.

Adverse selection/moral hazard. The Mossin-Pratt model assumes that there are no strategic interactions between the insurer and the agents, and that the insurer can observe the risk exposure of agents. Relaxing these assumptions, it is well known from basic asymmetric information theory that there may be a separating equilibrium in which high-risk agents purchase full coverage while low-risk agents purchase partial coverage. Hence, if wealth increases the chances of being high-risk, wealthier individuals are more likely to choose high coverage contracts. However, as mentioned above, the estimations included controls for both objective and subjective risks and their possible interactions with wealth. Therefore, adverse selection and/or moral hazard should not explain that insurance is a normal good.

Wealth-dependent risk aversion. The Mossin-Pratt model assumes that risk preferences are independent of wealth. However, the wealthy would purchase more insurance if they were, for a given wealth, more risk averse than the poor. This would counteract the DARA effect. However, this hypothesis seems implausible: rich people are usually found to be less risk averse for a given wealth (Guiso and Paiella 2008, Chiappori and Paiella 2011). Moreover, this hypothesis would contradict our other result that the demand for risky assets increases with wealth, and thus it is unlikely to explain the insurance-portfolio puzzle.

[58] See for example the literature on low agricultural insurance uptake in developing countries due to liquidity constraints (e.g. Liu and Myers 2016). We note, however, that liquidity constraints can also exacerbate insurance demand and the DARA effect (Gollier 2003).

Overall, we conclude that none of the proposed explanations based on standard theory is convincing at explaining the insurance-portfolio puzzle fully.

7.2 Behavioral Theories

We now discuss whether alternative theories relying on bounded rationality and psychology may explain the insurance-portfolio puzzle.

Prospect theory. According to prospect theory (see Kahneman and Tversky 1979, as well as e.g. Barberis 2013 and Barseghyan et al. (2013) for applications to finance and insurance), two decisions pertaining to different domains need not be conceived as similar even when they reflect an opposite risk retention tradeoff. Thus, one may expect prospect theory to explain the puzzle if it is assumed that portfolio decisions belong to the gain domain, while insurance decisions belong to the loss domain. This intuition, however, seems incomplete. First, the two decisions entail gains and losses and it is unclear why they would belong to different domains. Second, even if the two decisions belong to different domains, prospect theory would have to be extended to account for the opposite effect of wealth in each domain.

Risk (mis)perception. Suppose that the rich are more optimistic than the poor about financial risks, but that they are more pessimistic about insurable risks. This hypothesis implies that the rich invest more in risky assets and at the same time demand more insurance than the poor, thereby explaining the insurance-portfolio puzzle. However, we find limited evidence for this hypothesis in the data: Although the correlations between (liquid or financial) wealth and i) expectations about the stock market and ii) expected (auto and home) damages are positive, they are small (i.e. they do not exceed 0.05). Furthermore, we control for subjective risks and their possible interactions with wealth in the regressions.

Complexity. A related hypothesis concerns complexity and information. Financial and insurance products are notoriously complex (e.g. Carlin 2009). Handel and Kolstad (2015) show for instance that information frictions matter for health insurance choices, and accounting for these frictions leads to lower estimates of risk aversion. If the wealthy are more educated or have more financial literacy, they may be more willing to purchase complex financial and insurance products, and this could explain the insurance-portfolio puzzle. However, we controlled for education, financial literacy, and knowledge of car insurance and savings/debts. Overall, we consider that complexity and information frictions are unlikely to explain the puzzle.

Context-dependent preferences. Our empirical analysis shows that risk taking increases with wealth for portfolio decisions but decreases with wealth for insurance decisions. It may be argued that portfolio and insurance decisions concern different contexts, and that preferences differ in each context. Indeed, there is mounting evidence that risk preferences are not stable across contexts (e.g. Barseghyan, Prince and Teitelbaum 2011). If preferences are DARA in the financial context and IARA in the insurance context, then this would explain the puzzle. Although possible, this hypothesis implies that risk preferences would belong to a different "family" of utility functions in each context. This is an unusual assumption that remains to be further investigated.

Non-monetary benefits. Agents may derive a non-monetary benefit from insurance coverage. For instance, they may enjoy a higher quality of service, or a feeling of "peace of mind" (Chiappori and Salanié 2000, Kunreuther and Pauly 2005) when purchasing more insurance. Alternatively, agents may attach a sentimental value to the goods they insure, so that it may be optimal to over-insure in order to compensate for the loss in sentimental value when damages occur (Huang and Tzeng 2006). As a first attempt to capture these effects, we asked survey respondents the extent to which they attach a sentimental value to their car and whether they purchase extended warranties for peace of mind. As reported in Figure A1, we find no evidence that the rich care more about peace of mind, or assign a higher sentimental value to the good they insure. Therefore, there is no reason to be believe these non-monetary effects could explain the puzzle.

Regret avoidance. A few theoretical studies suggest that regret avoidance may affect the demand for insurance (e.g. Braun and Muermann 2004). Intuitively, one may buy more insurance to avoid regrets from being inadequately insured when damages occur, while one may buy less insurance to avoid regrets from paying insurance premiums when no damages occur. As far as we know, there is no empirical study on regret in insurance. As a first pass on evaluating the empirical relevance of this hypothesis, we asked survey respondents which factor drives their insurance decisions between "*(1) Making sure I would have enough coverage if I were to incur damages; (2) Making sure I would not pay too much for insurance if I end up not incurring any damages; (3) Both were equally important.*" The right panel of Figure A1 shows that the wealthy are more likely to respond (1) and less likely to respond (2). Thus, we find suggestive evidence consistent with the hypothesis that inadequate-insurance regrets by the wealthy may help explain why insurance appears to be a normal good.[59]

[59] We acknowledge that this empirical evidence does not provide unambiguous support to regret avoidance. In particular, it can be argued that the patterns in Figure A1 are consistent with standard theory if respondents interpret the question as reflecting the tradeoff between adequate coverage and premium payments.

8 Conclusion

Using micro level data, we find that households' risk taking decreases with wealth for insurance decisions but increases with wealth for portfolio decisions. This result is new to the literature, robust to different model specifications and data sources, and appears to be a puzzle as we failed to explain it with standard and behavioral theories. In contrast, other individual determinants (e.g. subjective expectations, risk attitude) and frictions (e.g. liquidity constraints, financial literacy) have the expected effect on both insurance and portfolio decisions. Moreover, a back-of-the-envelope calculation suggests that the puzzle is relevant and costly, representing at least 10% of the insurance premium. Finally, our analysis of "mistakes" suggests an asymmetric behavioral pattern: the poor are more likely to under-invest, while the rich are more likely to over-insure.

Our results have academic implications. In standard theory, starting with Pratt (1964) and Mossin (1968), the shape of the utility function of wealth drives many results in the finance and insurance literature. The standard assumption under which many classical predictions have been derived is DARA (Gollier 2001, Dionne 2013). Our empirical finding that insurance is a normal good is not consistent with DARA and thus challenges this literature. Further, the insurance-portfolio puzzle we identify suggests that the standard model is incomplete. In particular, portfolio and insurance decisions may need to be modeled differently, and not simply as an opposite risk retention tradeoff. Our paper also contributes to the behavioral insurance literature by identifying a new puzzle and an asymmetric pattern of mistakes in financial decisions. These results suggest that the similarities but also the differences between portfolio and insurance decisions need to be investigated further.

We now discuss possible macro implications. In the last 50 years, the growth of the insurance industry has far exceeded that of GDP, so that this industry has become increasingly important in the world economy (Browne, Chung and Frees 2000, OECD 2016). However, the relationship between insurance and economic development is still not well understood (Loubergé 2013, Outreville 2013). Our finding may contribute to understand better the demand-side drivers of insurance growth. In particular, the growth in the insurance sector is typically explained by the positive effect of an increase in the value of the goods (Beenstock, Dickinson and Khajuria 1988) and of a decrease in insurance loading factors over time (Szpiro 1986) that would dominate the negative effect of risk preferences. Our empirical results suggest however that the last effect is also positive: all else equal, agents purchase more insurance when they become wealthier.

We conclude with a discussion of possible policy implications. If the wealthy over-insure and the poor under-invest because of behavioral mistakes, then this may call for paternalistic interventions. As extensively discussed in the behavioral policy literature, such interventions are controversial. In particular, it is difficult to demonstrate that a specific behavior is a mistake and that it justifies public interventions. For instance, the wealthy may “feel good” about over-insuring and that feeling should matter for welfare analysis. Finally, a policy addressing the insurance-portfolio puzzle would aim at getting the poor to invest more aggressively and the rich to insure less, thus making the public more exposed to risks. Such a policy could prove difficult to defend.

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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: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Distributions of Wealth and Share of Risky Assets

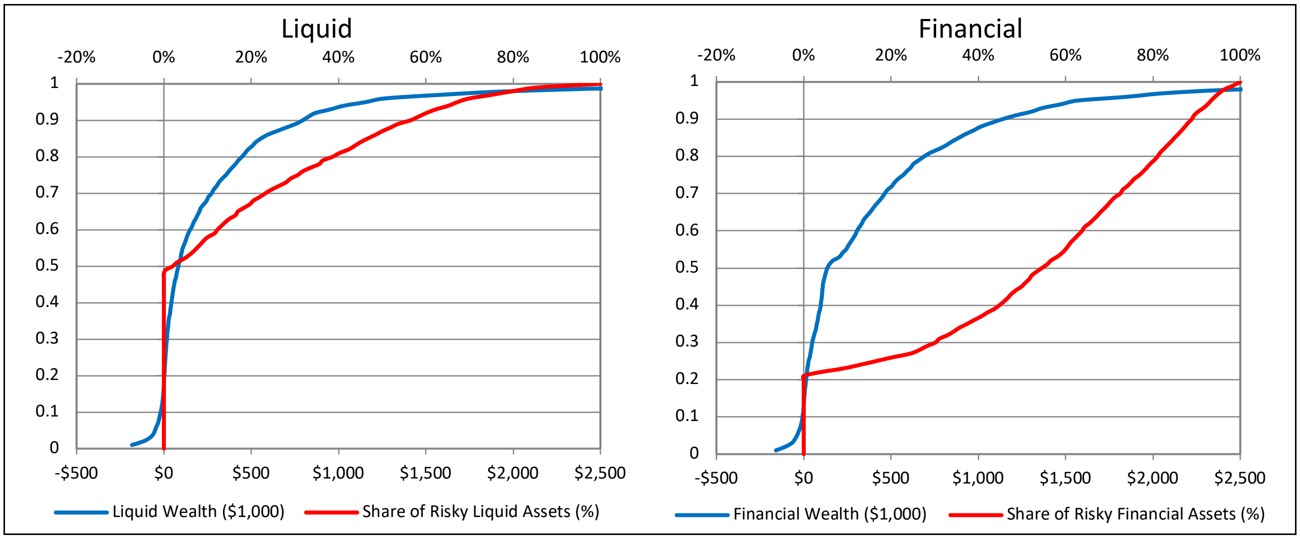
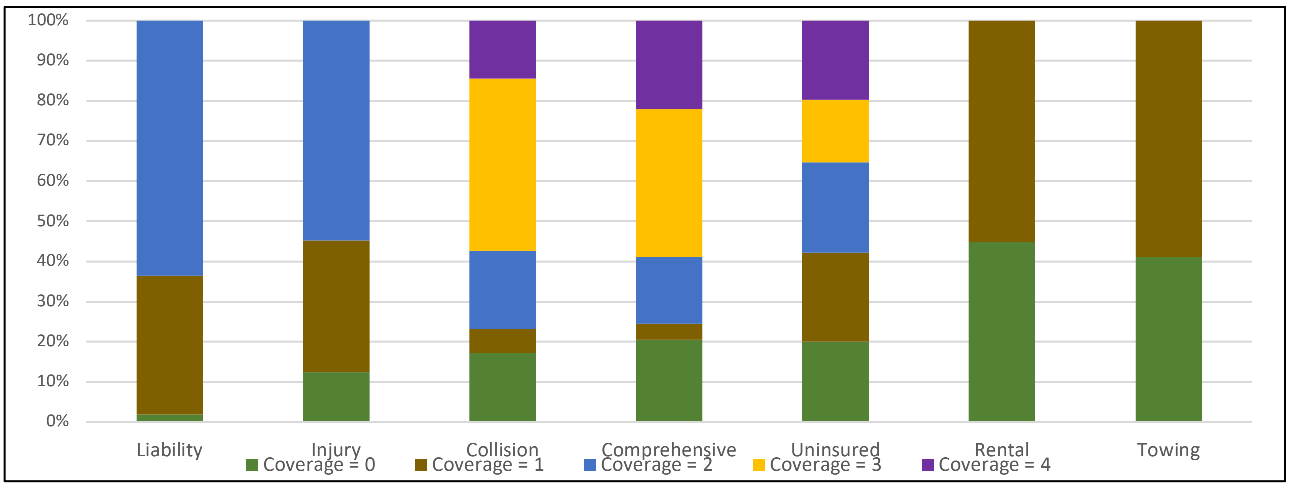
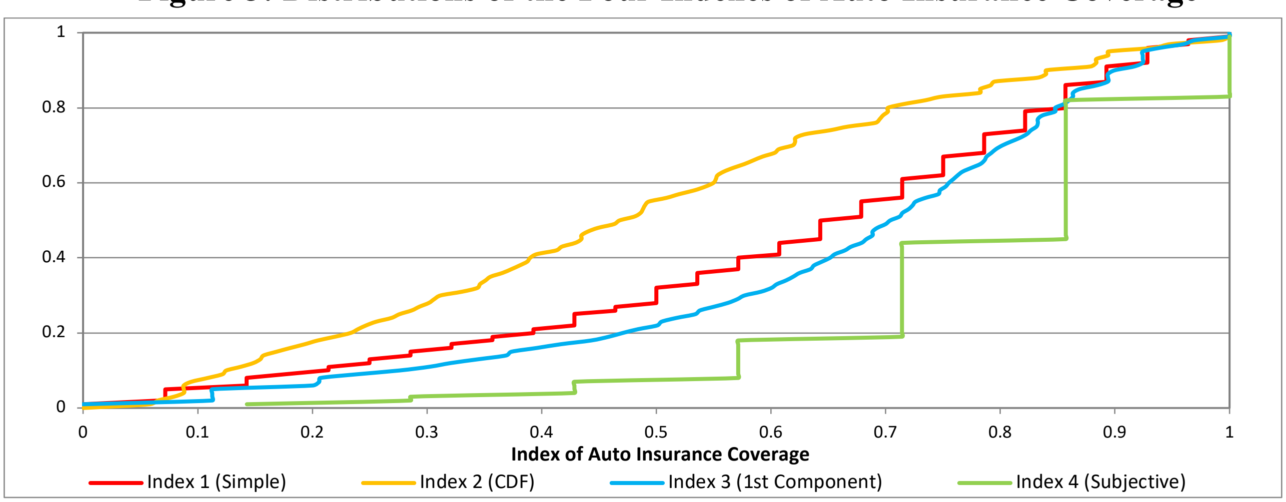


Figure 2: Components of Car Insurance Coverage



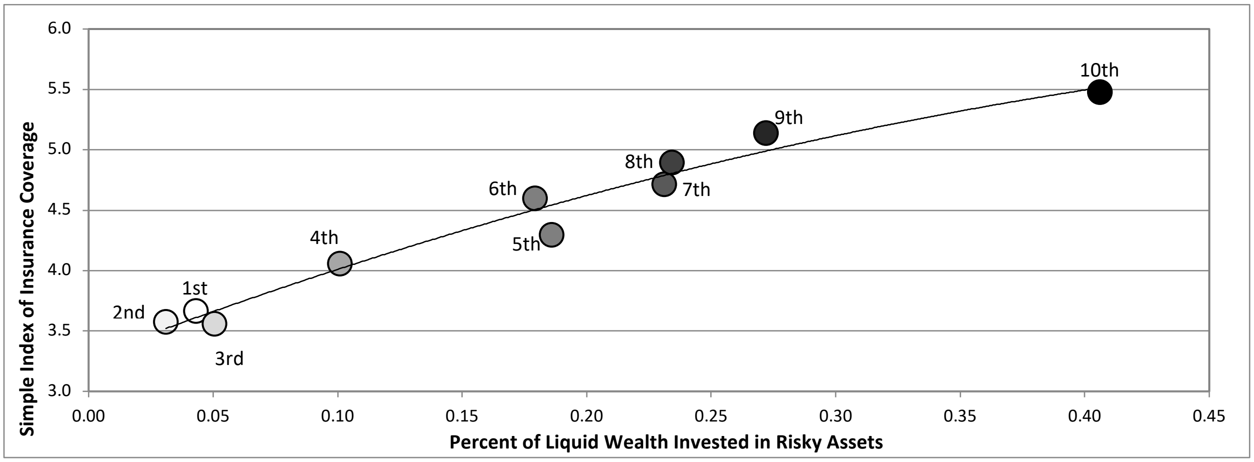
Liability: 0=No coverage, 1=Legal minimum, 2=More than legal minimum. **Injury**: 0=No coverage, 1=Legal minimum, 2=More than legal minimum. **Collision**: 0=No coverage, 1=deductible>$1,000, 2=$501<deductible<$1,000, 3=$251<deductible<=$500, 4=deductible<=$250. **Comprehensive**: 0=No coverage, 1=deductible>$1,000, 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



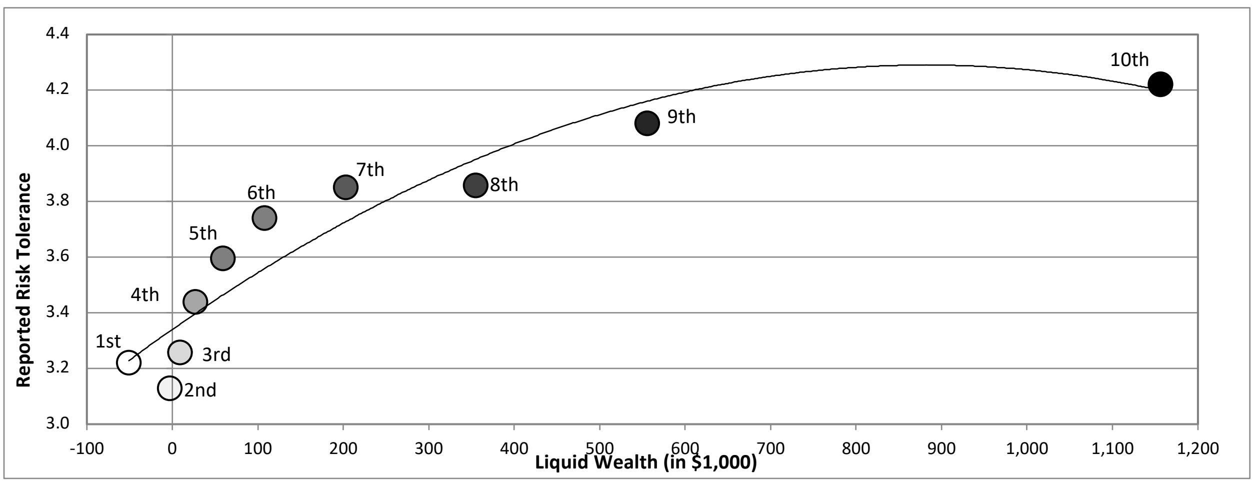
Each index has been normalized to 1 for comparison.

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



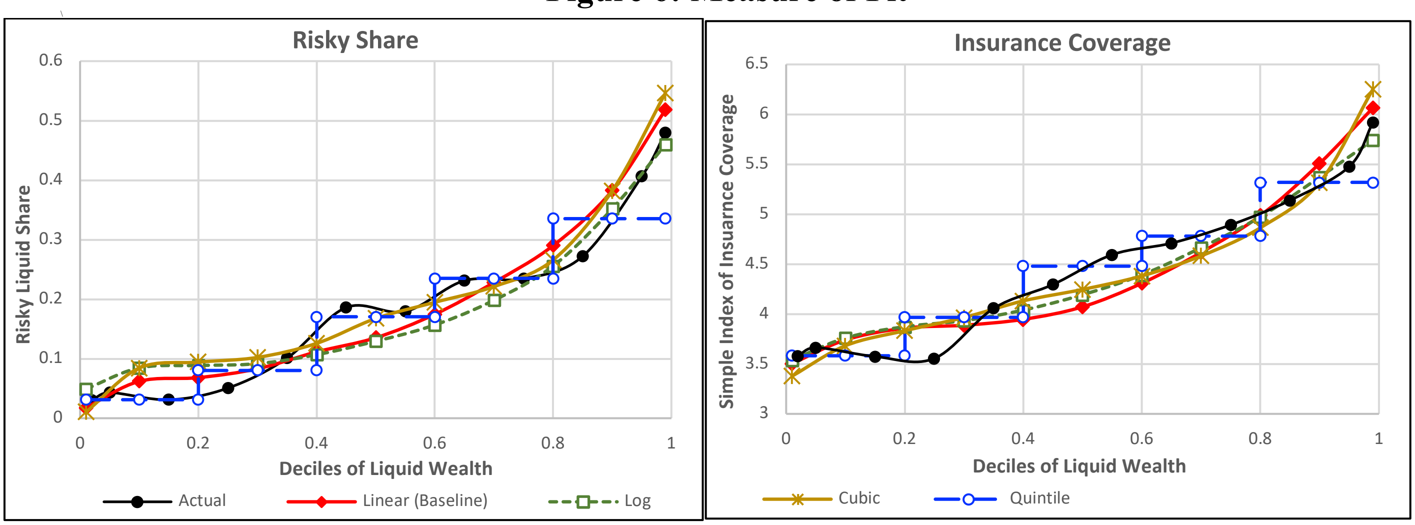
Each dot corresponds a decile of liquid wealth.

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



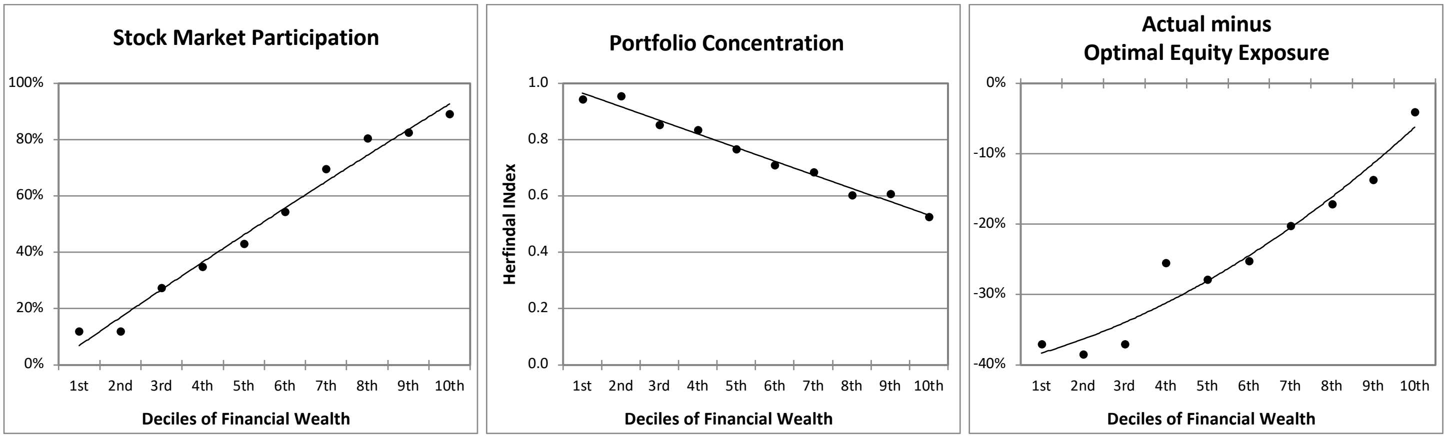
Each dot corresponds a decile of liquid wealth.

Figure 6: Measure of Fit



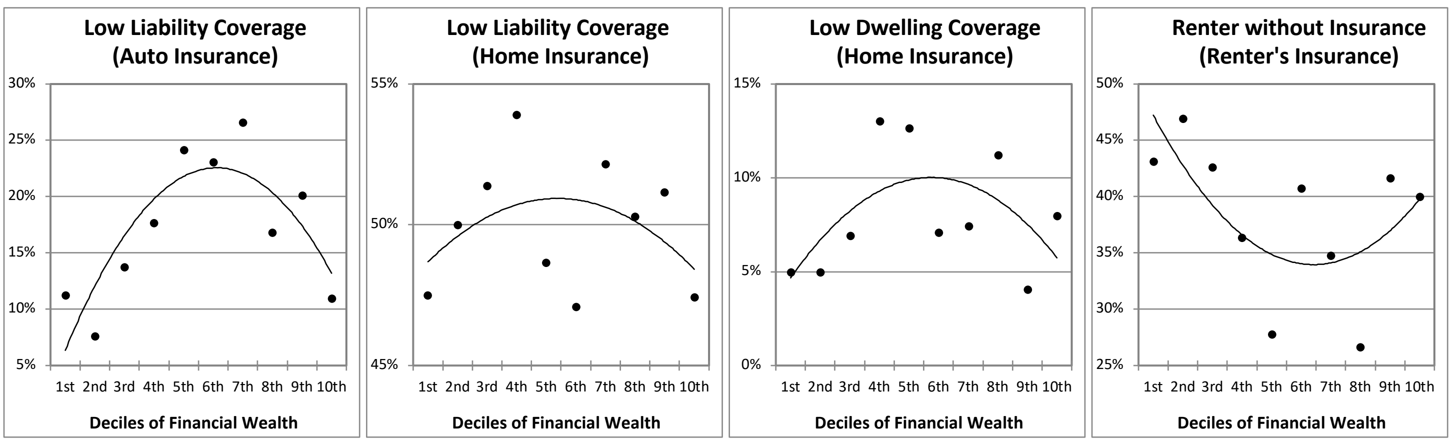
Actual: Average for respondents in each decile of wealth. **Linear**, **Log**, **Cubic**, **Quintil**e correspond to predictions from the models in Table 12 at each decile of wealth (the other variables are taken at their medians).

Figure 7: Measures of Investment Mistakes



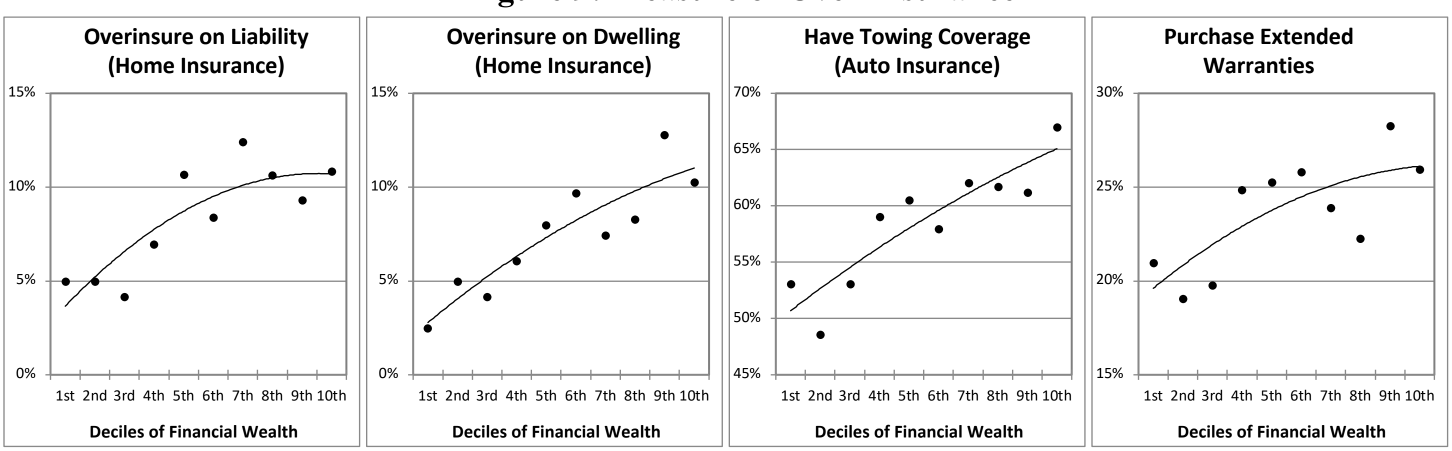
Stock Market Participation: Percentage of respondents in each decile of financial wealth who report owning stock directly or indirectly in pooled investment funds.
Portfolio Concentration: Herfindal index of the respondent's portfolio when decomposed in 6 categories: cash, stocks, bonds, Treasury bills, Treasury inflation protected securities (TIPS), and real estate investment trusts (REIT). Average for each decile of financial wealth.
Actual minus Optimal Equity Exposure: Percentage of liquid assets the respondent actually owns in stocks minus the percentage of stocks the respondents should own given his age according to the optimal life-cycle asset allocation of Gomes and Michealides (2005). Average for each decile of financial wealth.

Figure 8: Measures of Under-Insurance



Low Liability Coverage (Auto Insurance): The respondent purchased the minimum auto liability coverage required by law, this minimum is less than half of the respondent's exposed assets (i.e. all assets absent retirement savings), and the respondent does not have an umbrella insurance. Average for each decile of financial wealth.
Low Liability Coverage (Home Insurance): The home insurance liability coverage is less than half of the respondent's exposed assets and the respondent does not have an umbrella insurance. Average for each decile of financial wealth.
Low Dwelling Coverage (Home Insurance): The dwelling coverage is less than half of the replacement cost. Average for each decile of financial wealth.
Renter without Insurance (Renter's insurance): The respondent is a renter and has not purchased renter's insurance. Average for each decile of financial wealth.

Figure 9: Measure of Over-insurance



Over-insurance on Liability (Home Insurance): The home insurance liability coverage is more than 25% over the respondent's exposed assets (i.e. all assets absent retirement savings). Average for each decile of financial wealth. **Over-insurance on Dwelling (Home Insurance)**: The dwelling coverage is more than 25% over the replacement cost. Average for each decile of financial wealth. **Have Towing Coverage (Auto Insurance)**: The respondent purchased towing coverage. Average for each decile of financial wealth. **Purchase Extended Warranties:** The respondent purchased insurance or extended warranties when purchasing new appliances (such as electronics or home appliances) at least occasionally. Average for each decile of financial wealth.

Appendix A: Additional Tables

Table A1: 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	$I_{i,1}^{-}$	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** : $I_{i,1}^{-}$ = Simple index $I_{i,1}$ absent any liability protection.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: 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)	0.013** (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 A3: 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 A4: 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*** (0.058)	0.168*** (0.018)	**Ln Wealth**	392.935*** (52.727)	151.601*** (16.009)	**Wealth**	0.845*** (0.217)	0.633*** (0.070)	**Wealth 1st Quintile**	-0.854*** (0.273)	-0.354*** (0.047)
	—	—		—	—	**Wealth Squared**	-0.301** (0.146)	-0.255*** (0.043)	**Wealth 2nd Quintile**	-0.497** (0.231)	-0.200*** (0.032)
	—	—		—	—	**Wealth Cubed**	0.054** (0.023)	0.035*** (0.006)	**Wealth 4th Quintile**	0.284 (0.194)	0.096*** (0.027)
	—	—		—	—		—	—	**Wealth 5th Quintile**	0.800*** (0.304)	0.210*** (0.026)
Insurance Premium	0.020 (0.013)	—		0.020 (0.013)	—		0.020 (0.013)	—		0.021* (0.013)	—
Car Value	0.016*** (0.004)	—		0.015*** (0.004)	—		0.015*** (0.004)	—		0.015*** (0.004)	—
Objective Risk Auto	0.050 (0.058)	—		0.051 (0.058)	—		0.053 (0.058)	—		0.053 (0.058)	—
Zip Density	-0.310 (8.248)	-0.525 (1.121)		-0.302 (8.248)	-0.526 (1.121)		-0.319 (8.198)	-0.396 (1.132)		-0.332 (8.249)	-0.765 (1.063)
Age	0.010*** (0.003)	-0.002** (0.001)		0.008** (0.003)	-0.002** (0.001)		0.009*** (0.003)	-0.003** (0.001)		0.010*** (0.003)	-0.004*** (0.001)
Gender	0.058 (0.083)	-0.011 (0.020)		0.059 (0.085)	-0.010 (0.020)		0.062 (0.083)	-0.005 (0.019)		0.054 (0.083)	-0.005 (0.019)
Married	-0.038 (0.088)	0.052** (0.021)		-0.040 (0.088)	0.053** (0.021)		-0.046 (0.088)	0.031 (0.021)		-0.063 (0.089)	0.028 (0.021)
Have Kids	0.109 (0.081)	0.022 (0.020)		0.113 (0.080)	0.021 (0.020)		0.107 (0.081)	0.022 (0.019)		0.102 (0.082)	0.016 (0.019)
Black	0.007 (0.150)	-0.029 (0.039)		0.008 (0.146)	-0.030 (0.040)		0.007 (0.150)	-0.027 (0.039)		0.010 (0.149)	-0.018 (0.040)
Latino	-0.218 (0.159)	-0.014 (0.037)		-0.222 (0.160)	-0.014 (0.038)		-0.218 (0.159)	-0.006 (0.036)		-0.237 (0.159)	-0.013 (0.037)
Unemployed	-0.246 (0.287)	-0.067 (0.060)		-0.245 (0.291)	-0.066 (0.060)		-0.252 (0.287)	-0.076 (0.056)		-0.272 (0.283)	-0.085* (0.050)
High Education	0.182** (0.088)	0.070*** (0.021)		0.179** (0.085)	0.071*** (0.022)		0.189** (0.088)	0.072*** (0.021)		0.194** (0.089)	0.071*** (0.021)
Low Education	-0.308*** (0.096)	-0.073*** (0.023)		-0.312*** (0.098)	-0.074*** (0.023)		-0.300*** (0.097)	-0.058*** (0.022)		-0.276*** (0.096)	-0.054** (0.022)
Credit Score	0.018 (0.032)	0.033*** (0.008)		0.022 (0.030)	0.031*** (0.008)		0.012 (0.032)	0.028*** (0.008)		0.007 (0.032)	0.017** (0.008)
Subjective Risk Auto	0.167*** (0.047)	—		0.160*** (0.051)	—		0.164*** (0.047)	—		0.156*** (0.047)	—
Subjective Risk Stock	—	0.303** (0.127)		—	0.298** (0.126)		—	0.307** (0.125)		—	0.427*** (0.101)
Low Financial Literacy	-0.243** (0.097)	-0.076*** (0.024)		-0.235** (0.096)	-0.075*** (0.025)		-0.241** (0.097)	-0.076*** (0.023)		-0.247** (0.097)	-0.074*** (0.023)
Know Car Insurance	0.269*** (0.027)	—		0.265*** (0.028)	—		0.268*** (0.027)	—		0.263*** (0.027)	—
Know Savings and Debts	—	0.020* (0.012)		—	0.021* (0.012)		—	0.016 (0.012)		—	0.020* (0.011)
Financial Liquidity	0.528*** (0.136)	0.234*** (0.035)		0.507*** (0.143)	0.236*** (0.035)		0.492*** (0.139)	0.176*** (0.034)		0.401*** (0.144)	0.117*** (0.035)
Risk Tolerance	-0.089*** (0.025)	0.041*** (0.006)		-0.091*** (0.026)	0.042*** (0.011)		-0.090*** (0.025)	0.038*** (0.006)		-0.087*** (0.025)	0.037*** (0.006)
Constant	1.790*** (0.287)	-0.488*** (0.066)		-2671.54*** (358.691)	-1031.90*** (108.903		1.847*** (0.289)	-0.396*** (0.066)		2.177*** (0.322)	-0.129* (0.071)
Correlation (ρ_{IR})	0.073** (0.028)			0.075** (0.028)			0.073** (0.028)			0.074** (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 A5: 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 A6: 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 A7: Homeowner Insurance									
	Data 2015 & 2016			Data 2015			Data 2016		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Replacement cost†	231.31	200.00	179.53	231.30	200.00	164.91	231.31	182.00	193.08
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†	217.55	180.00	169.14	219.75	197.50	171.33	215.37	170.00	167.06
Personal property coverage†	84.88	50.00	89.90	89.70	50.00	99.65	80.125	50.00	78.88
Liability coverage†	242.11	100.00	492.62	253.02	100.00	525.82	231.43	100.00	458.00
Have flood insurance	0.12	0.00	0.32	0.13	0.00	0.33	0.11	0.00	0.31
Have earth movement insurance	0.08	0.00	0.27	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	0.32	0.11	0.00	0.31	0.13	0.00	0.33
Have umbrella insurance	0.20	0.00	0.40	0.22	0.00	0.41	0.19	0.00	0.39
Simple index $I_{i,1}$	3.37	3.08	1.17	3.40	3.17	1.17	3.34	3.08	1.17

† 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 A8: Homeowner and Renter Insurance Wealth = Liquid wealth, $I_{i,1}$ = Simple index of coverage, R_i = Share of risky liquid assets				
	Model 1 with Homeowners		Model 2 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 (0.081)	—	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

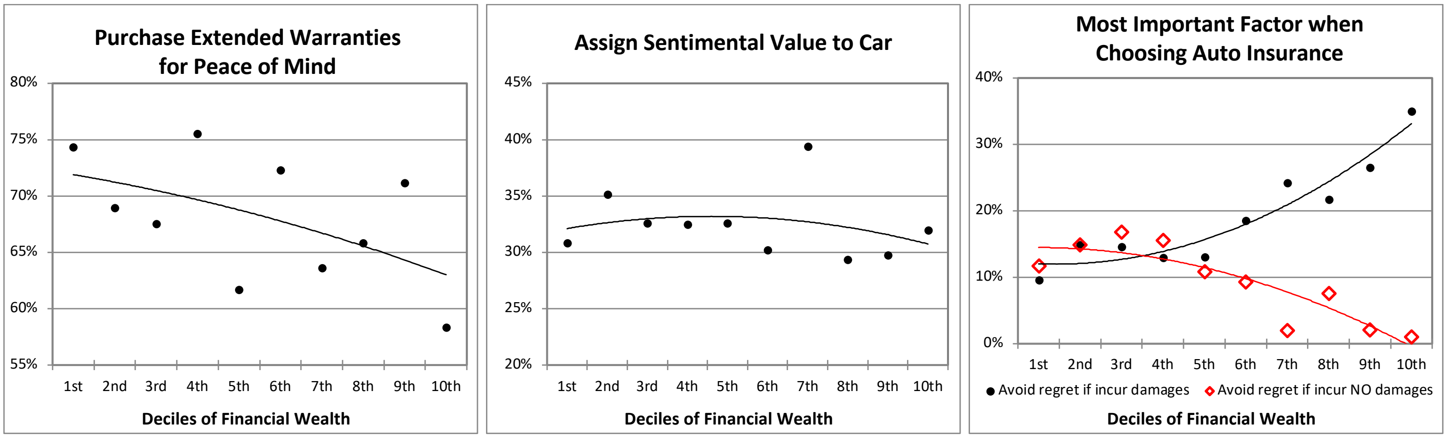
Table A9: French Data Wealth = Liquid wealth, $I_{i,1}$ = Dummy equal to 1 when the insurance contract is "Tous Risques" and 0 when "Au Tiers", R_i = Share of risky liquid assets		
	$I_{i,1}$	R_i
Wealth (100kFF)	0.042*** (0.009)	0.106*** (0.008)
Insurance Premium	3.864** (1.946)	—
Original Car Price	0.907*** (0.160)	—
Car Age	-0.196*** (0.013)	—
Original Car Price * Car Age	-0.068*** (0.017)	—
Objective Risk (Bonus-Malus)	0.018*** (0.001)	—
High Density	0.280*** (0.023)	0.092*** (0.016)
Age	0.011*** (0.001)	0.017*** (0.001)
Gender	0.146*** (0.026)	-0.071*** (0.018)
Unemployed	-0.361*** (0.051)	-0.175*** (0.038)
Credit Worthy	0.284* (0.145)	0.671*** (0.175)
Constant	2.319*** (0.217)	-2.274*** (0.177)
Correlation (ρ_{IR})	0.141*** (0.017)	
Observations	24,642	
AIC	42,352.4	

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

Table A10: Auxiliary Price Model Wealth = Liquid wealth, $I_{i,1}$ = Simple index of coverage	
	Insurance Premium ($100)
	$I_{i,1}$
$I_{i,1}$ Simple index of coverage	0.972** (0.046)
Age	-0.002*** (0.001)
Gender	0.001 (0.028)
Objective Risk Auto	2.550*** (0.201)
Subjective Risk	0.015 (0.151)
Car Value	0.010*** (0.002)
Zip Density	1.514*** (0.288)
Credit Score	-0.052** (0.105)
Married	0.064 (0.027)
Have Kids	0.162 (0.256)
Black	1.004* (0.581)
Latino	0.772* (0513)
Unemployed	-0.208 (0.737)
High Education	-0.155 (0.287)
Low Education	0.145 (0.316)
Wealth	-0.044 (0.257)
Low Financial Numeracy	0.785** (0.331)
Know Car Insurance	-0.212** (0.093)
Risk Tolerance	0.082 (0.080)
Financial Liquidity	0.050 (0.042)
Constant	8.730*** (0.796)
Observations	1806
Adjusted R2	0.230

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

Figure A1: Behavioral Factors



Purchase Extended Warranties for Peace of Mind: Respondents who purchased extended warranties at least occasionally are asked "*Why do you purchase insurance or extended warranty on appliances? (1) For peace of mind (2) It is worth the money (3) Other (please specify).*" The figure shows the proportion who selected (1).
Assign Sentimental Value to Car: Respondents are asked: "*Other than any financial considerations, to what extent are you "sentimentally" attached to the vehicle you insured?*" Responses are measured on a Likert scale from 1 (No sentimental attachment) to 7 (Very strong sentimental attachment). The Figure shows the percentage of responses above 4.
Most Important Factor when Choosing Auto Insurance: Respondents are asked: *"When you chose your auto insurance coverage, what was the most important factor? (1) Making sure I would have enough coverage if I were to incur damages (2) Making sure I would not pay too much for insurance if I end up not incurring any damages (3) Both were equally important.*" The figure shows the proportion of respondents who chose (1) (black dots) and (2) (red diamonds).

Appendix B: Theoretical Background

B.1 The 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 indemnity αL in case of loss L. The insurance premium is equal to $\alpha\pi$ where π is the full insurance premium. The agent decides the level of insurance coverage α which maximizes expected utility given a strictly increasing, concave and twice differentiable 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 coinsurance demand model à la Mossin (1968) is equivalent to Pratt (1964)'s portfolio decision model, as is well known (Gollier 2001) and as stated in the Introduction and Section 7. In the portfolio model, a is the amount invested in (net) risky assets, 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, i.e. $E\tilde{X} > 0$. Equivalently, in the insurance demand model, 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 wealth effects. It is well known that a increases in wealth w_0 iff u is DARA (Pratt 1964). To see that, using standard comparative statics techniques, a increases in w_0 iff $E\tilde{X}u'[w_0+a\tilde{X}]$ increases in w_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 coverage α decreases in wealth iff u is DARA (Mossin 1968).

B.2 Insurance and portfolio decisions

We now consider a model in which insurance and portfolio decisions are made simultaneously. Using the notation 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. Following the isomorphism between insurance and portfolio decisions (see B.1), we can interpret a and b as insurance and portfolio decisions respectively (i.e., an increase in a means less insurance demand and an increase in b means more investments in risky assets). This comparative statics analysis with multiple decisions is difficult in general. Here, we only consider "small risks" (Samuelson 1970). Assuming "small risks" imposes a strong restriction on the admissible set of probability distributions. This restriction implies that a second-order approximation is valid in the sense that it leads to the same solution as the general problem (5). The approximation yields:

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

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

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

Note that the above expression shows that a is equal to two terms: first, a standard risk retention term, namely $\frac{E\tilde{X}}{E\tilde{X}^2}\frac{u'(w)}{-u''(w)}$, minus a second term $b\frac{E\tilde{X}\tilde{Y}}{E\tilde{X}^2}$. Consistent with the discussion in Section 7, this second term can be interpreted as an (endogenous) background risk effect induced by the portfolio decision b.

We now assume that the random variables $\tilde{X}$ and $\tilde{Y}$ are independent, with $E\tilde{X} > 0$ and $E\tilde{Y} > 0$. 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 in brackets in (7) is positive. This shows that a is positive, and increases with wealth iff $\frac{u'(w)}{-u''(w)}$ increases with wealth, namely iff DARA. This implies that insurance demand decreases everywhere with wealth iff DARA and that the demand for risky assets increases everywhere with wealth iff DARA. Hence, the standard wealth effects are preserved in this case even if portfolio and insurance decisions are made simultaneously.

B.3 Insurance and savings decisions

We now study a standard two-period 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 denotes savings. 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 $E\tilde{X}u''[s(w) + a(w)\tilde{X}] \geq 0$. Yet we have seen above in Appendix B.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, i.e. $s'(w) > 0$, insurance demand decreases with wealth iff DARA, as in the simple insurance demand model (2). Aura, Diamond and Geanakoplos (2002) show that savings is indeed always a normal good in this 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.

B.4 Insurance demand with wealth-dependent loss

Next, we consider an insurance model in which the loss may depend on wealth (see e.g. Szpiro 1986). For simplicity, we assume that the distribution of the loss is binary, that is, either the agent loses $L(w)$ with probability p or he loses nothing. Note that the loss is now denoted $L(w)$, so that we make explicit 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:

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

We restrict further the model and consider a common CRRA utility function, i.e. $u[w] = (1-\gamma)^{-1}(w^{1-\gamma})$ with $\gamma > 0$. In this case, the problem of the agent can be rewritten

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

Note that this expression is equivalent to the Mossin model above 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 full liability insurance (i.e. $L(w) = w$), then wealth has no effect on insurance coverage. More generally, consistent with the statement in Section 7, the effect of wealth is positive iff the wealth-elasticity of the insured good, i.e. $\frac{wL'(w)}{L(w)}$, is greater than 1.