Countercyclical Risk Aversion: Evidence from 10 Million Auto Insurance Transactions in China

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Abstract

Whether risk aversion is time varying and countercyclical is central to modern asset pricing, yet evidence remains limited and is based mainly on experimental, survey, or aggregate stock market data. We provide individual-level evidence from 10 million Chinese auto insurance contracts from 2011 to 2017, estimating policyholders' risk aversion from deductible choices. We find that risk aversion is time varying and countercyclical. The estimates are negatively related to lottery and stock trading, positively related to insurance sales and bond trading, and vary with psychological factors, including seasonal mood, "zodiac year," and calendar events.

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I. Introduction

One leading explanation of various asset pricing puzzles is time-varying risk aversion (e.g., Campbell and Cochrane (1999)). In bad times with high marginal utility, investors tend to become more risk averse. This countercyclical nature of risk aversion can simultaneously help explain a large number of important yet puzzling facts—for example, return predictability, high equity premium, and excess volatility. It also helps explain the cross section of stock returns, bond returns, and foreign exchange rates (see, e.g., Zhang (2005), Wachter (2006), Chen, Collin-Dufresne, and Goldstein (2009), Verdelhan (2010), and Lustig, Roussanov, and Verdelhan (2014)).

While this feature is theoretically central, direct empirical evidence on whether risk aversion is in fact time varying and countercyclical is relatively scant, and existing studies rely on either experimental or survey data or stock market data. Cohn, Engelmann, Fehr, and Maréchal (2015) study this question by priming financial professionals with either a boom or a bust scenario. Guiso, Sapienza, and Zingales (2018) examine it using survey data on clients of one Italian bank. Another strand of the literature estimates time-varying risk aversion from stock market data, specifically S&P 500 index options. Aït-Sahalia and Lo (2000) recover state-price densities nonparametrically from a single year of options data (1993) and find that implied relative risk aversion varies across wealth states. Jackwerth (2000) extracts the implied risk aversion function over 1986–1995 and documents a dramatic shift around the 1987 crash. Rosenberg and Engle (2002) estimate monthly pricing kernels over 1991–1995 and find that implied risk aversion covaries with credit spreads. Kim (2014) uses stock market data directly to infer aggregate risk aversion. These market-based approaches recover a representative-agent pricing kernel.

In this paper, we complement the above studies by estimating risk aversion from a large panel of individuals using data from real-world, non–stock market transactions. In particular, using China's comprehensive auto insurance policy data, we estimate risk aversion following the approach of Cohen and Einav (2007). Our approach provides individual-by-individual, time-varying estimates of risk aversion from revealed preferences in actual market transactions. This approach distinguishes our study from experimental/survey-based methods, which typically measure risk aversion at a single point in time with small samples, and from stock-market-based approaches, which recover a representative-agent risk aversion parameter rather than individual-level heterogeneity.

We collect our dataset from China Insurance Information Technology Management (CIITC), a government agency that operates a centralized platform for nationwide insurance data in China. We collect about 10 million auto insurance policies from 2011 to 2017, representing the entire population of 200 million auto insurance policies in China.

In this paper, we find that the imputed risk aversion is consistent with established behavioral characteristics of risk preferences: it increases with individuals' age, is negatively related to lottery and stock trading activity in the region, and is positively related to regional insurance sales and bond trading. In an exploratory exercise, we find that aggregate risk aversion also predicts equity factor returns: higher risk aversion is associated with lower small-minus-big (SMB) returns, higher high-minus-low (HML) returns, and higher robust-minus-weak (RMW) returns.

More importantly, we find that risk aversion is countercyclical. In our baseline individual-level specification with person fixed effects, a one-standard-deviation decline in the quarterly GDP growth rate is associated with a 36.6% increase in relative risk aversion (RRA) in the log specification. The corresponding level estimate is an increase of 5.3, against a sample mean RRA of 15.112 and a median of 7.818. These estimates suggest that the variation in risk aversion in the time series is economically large. These results are consistent with the countercyclical variation in risk aversion.

The main finding is robust across different specifications: regressing risk aversion on lagged GDP growth; examining changes rather than levels of risk aversion; replacing GDP growth with the growth rates of retail sales, industrial production, real estate investment, and per capita consumption; using city-level GDP growth across all cities and within provincial capitals (under person or city fixed effects); aggregating to the province-quarter level; restricting to a quasi-balanced subsample of individuals who insure every year; and adopting alternative standard-error clustering schemes. A more fundamental concern is that the countercyclical pattern could be mechanically induced by the way we impute risk aversion rather than reflecting genuine preference variation. We provide evidence against the most plausible mechanical channels: reestimating risk aversion with time- and geography-specific expected-loss moments, holding each individual's premium rate fixed at its first-policy value in an illustrative experiment, and restricting the sample to narrow car age bands. The negative association remains in each of these exercises. However, the relation between risk aversion and GDP growth rates becomes statistically insignificant once we control for both person and year-quarter fixed effects. Because identification ultimately rests on aggregate time-series variation, these exercises cannot eliminate every market-wide confound that coincides with the business cycle.

We also explore how psychological forces may relate to variation in individuals' risk aversion. First, we test the seasonality of risk aversion. We follow Kamstra, Kramer, and Levi (2003) to measure the effect of seasonal affective disorder (SAD) using the number of nighttime hours during the fall and winter. The empirical evidence is consistent with risk aversion increasing with the length of the night and being higher in the fall and winter. Second, we study the influence of a particular superstition in China, called the "zodiac year effect," on risk aversion. For each person, the zodiac year occurs every 12 years. A common belief in China is that people are susceptible to encountering misfortune in the zodiac year and should therefore exercise caution to avoid experiencing a streak of bad luck (see also Fisman, Huang, Ning, Pan, Qiu, and Wang (2023)). Empirically, we find that an individual's imputed level of risk aversion increases in the zodiac year, consistent with the hypothesis that psychological forces could affect the level of time-varying risk aversion. Third, we examine calendar events and find that risk aversion is significantly higher around major national holidays, with the effect persisting into the post-event week; these associations are consistent with mood as a psychological component of time-varying risk aversion.

A growing body of research uses big data and alternative data to address questions in finance. Examples include Katona, Painter, Patatoukas, and Zeng (2025) and studies discussed in Goldstein, Spatt, and Ye (2021). Our paper contributes to this research by using insurance data, which are rarely available, to investigate asset pricing questions.

The rest of this paper is organized as follows. Section II describes the method of measuring risk aversion by the deductible choices from auto insurance data. Section III describes the data and the validity tests of risk aversion measures. Section IV examines whether risk aversion is time varying and countercyclical, including analyses that provide evidence against mechanical explanations, such as confounds from the auto insurance pricing reform and vehicle composition changes. This section also subjects the baseline countercyclical relationship to a battery of additional robustness checks. Section V examines psychological sources of risk aversion, across seasons, in zodiac years, and around calendar events. Section VI concludes.

II. Measuring Risk Aversion

A. Institutional Background

Although risk preferences are central to decisions under uncertainty and economic analysis, measuring risk aversion has been challenging. In recent years, eliciting risk aversion parameters from insurance data has received increasing attention (Cohen and Einav (2007), Sydnor (2010), Barseghyan, Prince, and Teitelbaum (2011), Einav, Finkelstein, Pascu, and Cullen (2012), Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2013)). In this paper, we follow Cohen and Einav (2007) to estimate individuals' levels of risk aversion by exploiting data on deductible choices in auto insurance contracts. The key assumption of using insurance data to estimate individuals' risk aversion is that individuals choose insurance contracts to hedge against risk.

Our main data source is the auto insurance platform of CIITC, which constructs and operates a centralized platform for sharing insurance data and information in China. The platform is publicly accessible and pools nationwide insurance data and information for motor vehicles in China.

In China, motor vehicles are mandatorily insured with "Automobile Mandatory Insurance" and optionally insured with motor vehicle commercial insurance, from which we can observe individuals' deductible choices. Commercial insurance includes primary insurance and optional insurance. Primary insurance covers loss insurance, Automobile Third Party Liability insurance, onboard personnel liability insurance, and theft insurance. For primary insurance, the default deductible rate is 15%. For optional insurance, individuals can choose a policy with a zero deductible rate. The deductible amount for the insurer of each policy equals the coverage multiplied by the loss rate multiplied by the deductible rate of the policy, in which the loss rate equals the ratio of realized loss to the coverage. Unlike the typical options of a regular deductible and a low deductible in Israel, for instance, individuals in China have the option to choose a policy with a zero deductible rate and an additional premium or a policy with a 15% deductible rate and no additional premium. All else equal, the individuals who choose the policy with a lower deductible rate despite the additional premium are more likely to have a higher level of risk aversion. The mandatory policy, the primary insurance structure, and the observable variation in deductible choices make the screening model of risk preferences plausible.

B. Benchmark Model of Deductible Choice

Let p, d, I, t denote the premium rate, the deductible rate, the coverage, and the duration of each additional policy, respectively. Consider the two deductible choices: (p_i^0, d_i^0) stands for the low deductible choice, where individual i needs to pay an additional premium $I_i \times p_i^0$ and the deductible rate d_i^0 is zero; and (p_i^1, d_i^1) stands for the high deductible choice, where individual i does not need to pay an additional premium ($p_i^1 = 0$) and the deductible rate d_i^1 is fixed at 15%. The loss rate of each claim is L, which is the ratio of realized loss to the coverage and is assumed to be lognormally distributed. Consistent with the key assumption in Cohen and Einav (2007), the annual claim rate of individual i, λ_i, is assumed to follow a Poisson process and to be known to individual i. In addition, there is no moral hazard in the model, so that λ_i is independent of the deductible choice.[1] Therefore, by definition, a risk-neutral individual i would choose the low

[1] If lower deductibles causally increased claiming behavior, the identification of r could be biased (Sydnor (2010)). To assess the empirical relevance of this concern, we examine within-person deductible switchers (Internet Appendix Table IA.I). Policyholders who move from a 15% to a zero deductible (Panel A) exhibit a decline in average claims per policy and in average sum loss per policy. Under moral hazard, a move to a zero deductible should increase claims, yet we observe the opposite. The decline alone, however, could reflect confounds common to any renewing policyholder, such as vehicle aging, driver learning, or mean reversion. We therefore compare the switchers with a control group of non-switchers who hold a 15% deductible in both years (Panel B), whose claims fall only slightly. Net of these confounds, the switchers' claims still fall rather than rise, the opposite of the moral-hazard prediction. More fundamentally, our paper focuses on the time-series variation in risk aversion rather than its level. Even if moral hazard introduces a level bias in estimated r, it would need to be time varying and correlated with GDP growth to bias our main

deductible choice if and only if the claim rate $\lambda_i \geq \frac{(p_i^0 - p_i^1)\times I_i}{(d_i^1 - d_i^0)\times I_i \times L} = \frac{p_i^0}{d_i^1 \times L}$.

For individual i with endowment wealth of w_i, the expected utility of a deductible choice (p_i, d_i) can be written as

$$v(p_i, d_i) = (1 - \lambda_i t_i)u(w_i - I_i p_i t_i) + \lambda_i t_i u(w_i - I_i p_i t_i - I_i L d_i), \tag{1}$$

where $u(w)$ is the utility function.

To estimate individuals' levels of risk aversion, the basic idea is that, when the expected utility is indifferent between the low deductible choice and the high deductible choice, it will provide a lower bound on the risk aversion of individuals who choose the low deductible choice and an upper bound on the risk aversion of individuals who choose the high deductible choice. Therefore, we can analyze the equation $v(p_i^0, d_i^0) = v(p_i^1, d_i^1)$ and proceed to calculate the expression of the claim rate as

(2)

$$\begin{aligned}\lambda = \lim_{t_i \to 0} & \frac{\frac{1}{t_i}(u(w_i - I_i p_i^0 t_i) - u(w_i - I_i p_i^1 t_i))}{u(w_i - I_i p_i^1 t_i - I_i L d_i^1) - u(w_i - I_i p_i^0 t_i - I_i L d_i^0) - u(w_i - I_i p_i^1 t_i) + u(w_i - I_i p_i^0 t_i)} \\ = & \frac{(p_i^0 - p_i^1) I_i u'(w_i)}{u(w_i - I_i L d_i^0) - u(w_i - I_i L d_i^1)}.\end{aligned}$$

By Taylor's expansion, we have

$$u(w - \epsilon) = u(w) - u'(w)\epsilon + \frac{1}{2}u''(w)\epsilon^2 + o(\epsilon^2). \tag{3}$$

Combining equations (2) and (3) and using the definition of absolute risk aversion, we can infer the

finding.

individual's level of absolute risk aversion as

$$r \equiv \frac{-u''(w)}{u'(w)} = \frac{\frac{p_i^0 - p_i^1}{\lambda(d_i^1 - d_i^0)} - E(L)}{\frac{d_i^0 + d_i^1}{2} I_i E(L^2)}, \tag{4}$$

where r stands for the individual's absolute risk aversion, and $E(L)$ and $E(L^2)$ are the first and second moments of the loss rate, respectively.

C. Estimating Absolute Risk Aversion

Based on individuals' deductible choices in the auto insurance data, (p_i, d_i) and I_i are observable. In particular, $d_i^0 = 0$, $d_i^1 = 0.15$, and $p_i^1 = 0$. We can therefore rewrite the formula for absolute risk aversion in equation (4) as

$$r = \frac{\frac{p_i^0}{0.15 \times \lambda} - E(L)}{0.075 \times I_i E(L^2)}. \tag{5}$$

In addition, we can estimate the mean and variance of the loss rate from the realized insurance claim data. For example, we randomly select about 10,000 claims; the fitted loss rate distribution is plotted in Internet Appendix Figure IA.I. The loss rate of claims is approximately lognormally distributed, as is typically assumed in the literature. In our sample dataset, the mean and variance of the loss rate are 0.02 and 0.00285, respectively.

In an econometric exercise, we use the observable data, denoted by x_i, from the deductible choices to estimate the annual claim rate and the absolute risk aversion of each individual i: (λ_i, r_i).

Assuming that (λ_i, r_i) is bivariate lognormally distributed, we can write the econometric model as

$$ln(\lambda_i) = x_i'\beta + \epsilon_i, \tag{6}$$

$$ln(r_i) = x_i'\gamma + \delta_i, \tag{7}$$

and the residuals ϵ_i and δ_i satisfy

$$\begin{pmatrix} \epsilon_i \\ \\ \delta_i \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\lambda^2 & \rho\sigma_\lambda\sigma_r \\ \\ \rho\sigma_\lambda\sigma_r & \sigma_r^2 \end{bmatrix} \right). \tag{8}$$

The variable λ_i in equation (6) and the variable r_i in equation (7) are treated as latent variables, since they are unobservable. We observe the realized number of claims and the deductible choices of individuals on the auto insurance platform. As is typically assumed, the number of claims of individual i is generated by a Poisson process:

$$Claims_i \sim Poisson(\lambda_i t_i). \tag{9}$$

In addition, individual i chooses the low deductible choice ($Choice_i = 0$) if and only if the risk aversion r_i is higher than the lower bound generated from the formula in equation (5) when $\lambda = \lambda_i$:

$$Pr(Choice_i = 0) = Pr\left(r_i > \frac{\frac{p_i^0}{0.15\times\lambda_i} - E(L)}{0.075\times I_i E(L^2)} \right) = Pr\left(e^{x_i'\gamma + \delta_i} > \frac{\frac{p_i^0}{0.15\times e^{x_i'\beta+\epsilon_i}} - E(L)}{0.075\times I_i E(L^2)} \right). \tag{10}$$

Based on the assumption in equation (9) and the result in equation (10), we can estimate the parameters β and γ from the auto insurance data and then recover λ_i and r_i. In practice, we use the

Markov chain Monte Carlo (MCMC) algorithm, specifically Gibbs sampling, to obtain the limiting distribution and then the posterior distribution of claims and choices. Finally, we obtain the estimated annual claim rate and the absolute risk aversion of each individual after 100,000 iterations. See the appendix in Cohen and Einav (2007) for details on the MCMC algorithm.

III. Insurance Data and Risk Aversion

A. Insurance Data

The original sample from the auto insurance platform of CIITC comprises 10 million policy-level records from 2011 to 2017, including all first-time and repeated applications. The sample was randomly drawn from the nearly 200 million policy-level records in the entire platform at the individual level: once an individual is selected into the sample, all of that individual's policies across the entire sample period are included.[2] This design ensures that we observe the complete insurance history for each sampled individual, which is essential for exploiting within-person variation and including person fixed effects. For each record, the data contain demographic characteristics of the applicant, car attributes, insurance clauses, and claims within the duration of the policy. Internet Appendix IA.1 reports a description of the fully detailed sample.

In this sample, auto insurance applications are aggregated on a quarterly basis for each applicant.[3] There are 2,951,145 unique applicants with 10,229,255 valid observations in the final sample and nearly 101,764 applicants, on average, in each province. The distributions of the final sample in each province are reported in Figure 1. Jiangsu and Zhejiang have the most applicants,

[2]The 5% sampling rate reflects the data access arrangement with CIITC at the time of data collection; we have verified that the sample is representative of the full population in terms of demographic and geographic distributions.

[3]For an individual with more than one vehicle in a given quarter, we select the vehicle with the highest value.

while Xinjiang and Tibet have the least. In addition, we collect the province-level and city-level macro outputs and consumption data, lottery sales data, stock trading volume, bond trading volume, and the total trading volume of capital assets from the Wind database.

[INSERT FIGURE 1 ABOUT HERE]

B. Summary Statistics

The summary statistics for the main variables are given in Table 1. The final sample includes 10,229,255 applicant-quarter observations, referring to applications of 2,951,145 individuals. The applicants' absolute risk aversion (ARA)—estimated by the approach described in Section II—has an average of 6.842×10^{-4} CNY^{-1}. It is about 4 times the estimate of 1.02×10^{-3} USD^{-1} in Cohen and Einav (2007) for auto insurance applicants and about 14 times the estimate 3.1×10^{-4} USD^{-1} in Gertner (1993) for television game show participants. Since the exchange rate of the US dollar to the Chinese CNY is between 6 and 7 from 2011 to 2017, our estimates are largely consistent with the literature.

[INSERT TABLE 1 ABOUT HERE]

We follow the standard risk aversion model to estimate the relative risk aversion of applicants by multiplying the absolute risk aversion by the annual consumption. Since the annual consumption data of applicants are unavailable, we instead use per capita annual consumption of the city in which the applicant lives. There are 8,997,276 observations of estimated relative risk aversion. The missing observations are due to the unavailability of consumption data in certain cities. The estimated relative risk aversion has an average of 15.112 and a median value of 7.818 with a standard deviation of 22.116, which is also of the same order of magnitude as the estimate of

14.84 in Cohen and Einav (2007) and 4.79 in Gertner (1993).

In addition to the risk aversion measures, the applicants in our sample are between 22 and 62 years old, with an average age of 38.3 years, and 72.3% of the applications are from male applicants. For the loss policies, the averages of the natural logarithms of premium and coverage are 7.225 and 11.452. The insured cars have been used for 2.914 years on average. The real quarterly GDP growth rate of provinces in our sample has an average of 8.7% with a standard deviation of 1.8%. As alternative macroeconomic indicators, the means of the real quarterly growth rate of industrial production, aggregate retail sales, and real estate investments in each province are 9.0%, 11.9%, and 12.4%, respectively. Per capita consumption has an annual growth rate of 8.4% with a standard deviation of 3.6%.

C. Validity of Risk Aversion Estimates

Although risk aversion has long been discussed in theoretical studies, quantitatively measuring individuals' risk aversion is not easy. A body of empirical studies measures risk preferences using hypothetical survey questions, such as Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011), Barsky, Juster, Kimball, and Shapiro (1997), and Guiso et al. (2018), or by television game show participation, such as Gertner (1993).

In this paper, we follow Cohen and Einav (2007) to estimate individuals' levels of risk aversion based on their deductible choices in auto insurance, from which we can study both the time-series and cross-sectional variations in risk aversion. As discussed in the previous section, our estimated absolute risk aversion and relative risk aversion are of the same order of magnitude as those estimates in the literature. We now further examine the validity of our estimated risk aversion from several angles.

First, we estimate panel regressions to test whether the estimated risk aversion is correlated with individuals' demographic characteristics. The results are reported in Table 2. We estimate panel regressions with no fixed effects or with year×quarter fixed effects, with the dependent variable being the absolute risk aversion measure, as reported in Columns 1 and 2, the log of the absolute risk aversion measure, as reported in Columns 3 and 4, the relative risk aversion measure, as reported in Columns 5 and 6, or the log of the relative risk aversion measure, as reported in Columns 7 and 8. In the Chinese auto insurance market, we do not find significant evidence supporting the inference that females are more risk averse than males. In the level regressions (Columns 1–2 and 5–6), male applicants even exhibit significantly higher absolute and relative risk aversion. However, in the log specifications (Columns 3–4 and 7–8), the male coefficients are economically small and statistically indistinguishable from zero, indicating that male and female applicants do not differ significantly in risk aversion. The estimated coefficients of age show an increasing pattern of individuals' risk aversion over the life cycle: individuals become more risk averse as they grow older. These findings together indicate that applicants' risk aversion increases with age.

[INSERT TABLE 2 ABOUT HERE]

We then investigate the correlation of our risk aversion measure with other risky asset preferences. A classic way to estimate individuals' risk aversion in the literature is to measure their preference for lottery choices, such as Donkers, Melenberg, and Van Soest (2001), Holt and Laury (2002), and Andersen, Harrison, Lau, and Rutström (2008). In another paper, Guiso et al. (2018) use the subjective choices of respondents on lotteries as the quantitative indicator of their risk preference. To validate our measure of risk aversion, we examine the correlation of our risk aversion measure with lottery sales growth. In each province, we average the risk aversion measure of applicants as the aggregate indicator of the province on a quarterly basis. We estimate the panel regression of the quarterly growth rate of lottery sales, which is calculated as the change in the natural logarithm of current lottery sales to the four-quarter-prior lottery sales within the province, on the aggregate risk aversion indicator in the province-quarter panel. We use the change in the natural log of aggregate lottery sales as the dependent variable to mitigate the influence of autocorrelation. The results are reported in Table 3. In Columns 1 and 2 of the bottom panel, the growth rate of lottery sales is negatively correlated with the aggregate absolute risk aversion of individuals. The estimated coefficient of $Ln(ARA)$ is -0.169, which is statistically significant with a t-statistic of -4.61. The relative risk aversion indicator $Ln(RRA)$ has an estimated coefficient of -0.140 with a t-statistic of -5.26, remaining statistically significant. The above results remain unchanged when we replace the explanatory variable with the raw variable of absolute risk aversion or relative risk aversion. The negative correlation between our risk aversion measures and the lottery sales growth rate is consistent with individuals being less likely to buy lotteries when they are more risk averse, in line with the literature.

[INSERT TABLE 3 ABOUT HERE]

In addition to lottery sales growth, we investigate the correlation of our risk aversion measure with individuals' preference for insurance. In each province, we calculate the quarterly growth rate of aggregate insurance sales as the log change from four-quarter-prior insurance sales to current total insurance sales within the province, including the sales of property insurance, life insurance, accident insurance, and health insurance. As in the analysis of lottery sales growth, we reestimate the panel regression of the quarterly growth rate of aggregate insurance sales on the aggregate risk aversion indicator in the province-quarter panel. We present the results in Columns 3 and 4 of Table 3. In Column 3 of the bottom panel, the estimated coefficient of $Ln(ARA)$ is 0.124, statistically significant with a t-statistic of 4.07. Column 4 also shows that the log of relative risk aversion is positively correlated with the change in the log of aggregate insurance sales, with an estimated coefficient of 0.111 and a t-statistic of 4.87. Again, the above results are robust when we replace the explanatory variable with the raw variable of absolute risk aversion or relative risk aversion. These results suggest that individuals with higher risk aversion tend to purchase more insurance policies.

We further validate our risk aversion measure by testing its correlation with household portfolio allocation across risky and riskless assets. Our test builds on the idea that investors with lower risk aversion hold more of their wealth in risky assets (Brunnermeier and Nagel (2008)). We study the time-varying allocation on stocks and bonds at the aggregate level within the province on an annual basis since quarterly data are unavailable. Relative stock trading (RelStock) is defined as the ratio of annual stock trading volume to the total trading volume of capital assets. Relative bond trading (RelBond) is defined as the ratio of annual bond trading volume to the total trading volume of capital assets. The capital assets here include stocks, funds, bonds, and warrants. Then we estimate the panel regressions of relative stock trading and relative bond trading on the aggregate risk aversion indicator in the province-year panel and report the results in Columns 5 to 8 of Table 3. Columns 5 and 6 of the bottom panel show that relative stock trading volume is negatively correlated with the log of absolute risk aversion with a coefficient of -0.196 and negatively correlated with the log of relative risk aversion with a coefficient of -0.142, both of which are statistically significant. In contrast, the relative bond trading volume is positively correlated with the log of absolute risk aversion with a coefficient of 0.184 and positively correlated with the log of relative risk aversion with a coefficient of 0.129, both statistically significant at the 10% level, as shown in Columns 7 and 8. The statistical significance of the above results gets stronger when we replace the explanatory variable with the raw variable of absolute risk aversion or relative risk aversion. In sum, the results are consistent with investors shifting from stocks toward bonds when risk aversion is high.

Lastly, as an exploratory exercise, we examine whether our risk aversion measures contain information about asset prices.[4] To explore this question, we construct monthly aggregate risk aversion series by averaging ARA and RRA (and their logarithms) across all individuals in each month and examine whether these series predict Chinese equity factor returns one month ahead. Table 4 reports the results. We regress six factor returns, including market return, market premium, SMB, HML, RMW, and conservative-minus-aggressive (CMA), on lagged aggregate risk aversion. The sample consists of 84 monthly observations, and we report t-statistics computed from heteroskedasticity-robust standard errors; given the short sample, the evidence is necessarily suggestive. ARA does not predict market returns or CMA but significantly predicts SMB (−0.554), HML (0.254), and RMW (0.309). The RRA-based regressions yield consistent results: RRA predicts SMB (−0.163), HML (0.075), and RMW (0.092). The log specifications (bottom panel of Table 4) deliver the same qualitative pattern. These findings suggest that when aggregate risk aversion is high, small-minus-big returns are lower, value-minus-growth returns are higher, and robust-minus-weak returns are higher. We caution, however, that aggregate risk aversion does not

[4] Beyond equity factor returns, we also examined, in untabulated tests, whether aggregate risk aversion predicts mutual fund flows and corporate bond credit spreads; the results are mixed and reinforce the exploratory nature of this exercise. Aggregate risk aversion bears no significant relation to quarterly net flows into equity, bond, money market, or composite funds. For AAA corporate bond credit spreads, higher risk aversion is associated with a counterintuitive narrowing of spreads, which likely reflects the institutional features of China's bond market: AAA-rated bonds are predominantly issued by state-owned enterprises with implicit government guarantees and thus behave as quasi-safe assets rather than instruments bearing meaningful default risk (Geng and Pan (2024)).

predict the aggregate market return itself,[5] which limits what the exercise contributes to the aggregate market-return predictability emphasized by Campbell and Cochrane (1999).

[INSERT TABLE 4 ABOUT HERE]

Our risk aversion measures are consistent with existing estimates in the literature. First, they are similar in magnitude. Second, our risk aversion measures increase with individuals' age. Individuals with higher risk aversion are less likely to buy lotteries and stocks but more likely to buy insurance and bonds, supporting the interpretation that our measure captures variation in risk preferences across asset classes. These results are also consistent with the domain generality in risky asset preferences (Einav et al. (2012)), which means that the relative ranking of individuals' risk preferences is stable across contexts. Lastly, higher aggregate risk aversion is associated with factor returns such as SMB, HML, and RMW.

IV. Time-Varying and Countercyclical Risk Aversion

A. Aggregate-Level Indication

In a seminal paper, Campbell and Cochrane (1999) build a consumption-based model with time-varying, countercyclical risk aversion at its core to jointly explain a number of important asset pricing phenomena. However, directly testing whether individuals' levels of risk aversion are time varying and countercyclical is challenging, even though the idea is appealing. The central challenge is how to measure individuals' risk aversion, especially the time-series risk aversion measures across years. To the best of our knowledge, there is no direct empirical evidence of time-varying

[5] Such non-results are common in predictive return regressions and unsurprising in our short monthly sample, given the fragility of aggregate return predictability and the low signal-to-noise ratio of the market return (Welch and Goyal (2008), Goyal, Welch, and Zafirov (2024)).

and countercyclical risk aversion based on transaction data. The closest result to this idea might be the study of Guiso et al. (2018), in which they used repeated surveys on the same investors in two years, 2007 and 2009, and found that investors' risk aversion increased after the 2008 global financial crisis. Andersen et al. (2008) conducted repeated field experiments to elicit the risk preferences of subjects over a 17-month period but did not detect a general tendency for variation in risk attitudes. Cohn et al. (2015) measured the risk aversion of financial professionals by their willingness to take financial risks in controlled experiments and compared the risk-taking behaviors across subjects in different scenarios. They found that subjects primed with a financial "bust" were substantially more fearful and risk averse than those primed with a financial "boom," thus supporting countercyclical risk aversion. Unlike these studies, the major advantage of using the deductible choices from auto insurance data to estimate risk aversion in this paper is that we can continuously estimate the risk aversion of each applicant over different years.

With continuous measures of individuals' risk aversion, we can first examine whether risk aversion fluctuates over time at the aggregate level.[6] Since our final sample is an approximately representative sample of all the motor vehicle users in China, we measure aggregate risk aversion by averaging the estimated risk aversion measures across all applicants. In Figure 2, we plot the aggregate absolute risk aversion and relative risk aversion together with macroeconomic indicators, including the aggregate GDP growth rate, aggregate retail sales growth rate, aggregate industrial production growth rate, and aggregate real estate investment growth rate. In Graph A, we can see that aggregate absolute risk aversion was nearly unchanged around 0.0005 before 2014 but began to increase in late 2015 and doubled to about 0.0010 in 2017. Aggregate relative risk aversion slightly

[6]The fluctuation of aggregate risk aversion could result from either the change in typical individuals' risk aversion or the change in the distribution of wealth among individuals with different levels of risk aversion, as indicated in Guiso et al. (2018). We focus on whether the individuals' risk aversion varies in time in this paper.

fluctuated from 8 to 10 before 2015 but increased rapidly in 2016 and fluctuated between 25 and 30 in 2017. Meanwhile, the aggregate quarterly GDP growth rate of China kept decreasing, although not monotonically, from 2011 to 2017 with a minimum of 6.7% in late 2016 and late 2017. Graph B shows that the quarterly growth rate of aggregate retail sales dropped from around 17% in 2011 to lower than 11% in 2016 and 2017. In Graph C, we see that the quarterly growth rate of aggregate industrial production also dropped from above 10% in 2011 to around 6% after 2015 with a minimum of 5.7% in the first quarter of 2016 when both aggregate absolute risk aversion and aggregate relative risk aversion began to increase rapidly. Again, as shown in Graph D, aggregate real estate investment increased substantially, with a growth rate higher than 30% in the first half of 2011, and then slowed down. In late 2015, the quarterly growth rate of aggregate real estate investment turned negative and then reversed. In these graphs, we find that macroeconomic indicators vary earlier and, more importantly, counter to risk aversion. The lagged reaction of risk aversion might be attributable to the general insensitivity of individuals to macroeconomic variations. Figure 2 thus offers preliminary evidence that risk aversion is time varying and countercyclical, as judged from its countervariation with macroeconomic indicators.

[INSERT FIGURE 2 ABOUT HERE]

Unlike the cross-sectional variation in risk aversion, the time-varying measure may be influenced by changes in aggregate auto insurance prices over time. For primary auto loss insurance in China, the default deductible rate is 15%. Individuals have the option to choose a policy with a zero deductible rate and an additional premium, which is 15% of the primary loss insurance premium. Thus, the price of the deductible choice is proportional to the price of the primary loss insurance. To address the concern regarding an aggregate price effect on individuals' deductible choice and risk aversion measures over time, we plot the number of loss insurance policies and the average premium rate in Figure 3. The figure shows that loss insurance policies increased steadily before 2014 but remained unchanged each year after 2015, although loss insurance sales are higher in the fourth quarter relative to other quarters. Regarding the loss insurance price, the average premium rate fluctuated around 1.5% before the second quarter of 2016 and then increased to about 1.85% in the first quarter of 2017 and decreased afterward. Even though the aggregate loss insurance price changed over time, meaning that the aggregate deductible choice price changed over time, indeed, we do not find a clear comovement between risk aversion measures and the insurance price. In addition, the loss insurance premium is included in the estimation procedure of individuals' risk aversion parameter. For these reasons, aggregate-level time-varying and countercyclical risk aversion is unlikely to be explained by the change in the auto insurance price.

[INSERT FIGURE 3 ABOUT HERE]

B. Individual-Level Regressions

In a previous section, we have shown that aggregate risk aversion can fluctuate over time as well as in the opposite direction of economic trends, which are evaluated by macroeconomic indicators. To study the quantitative relationship between individuals' risk aversion and economic indicators, we further estimate panel regressions with the GDP growth rate and with alternative economic indicators at the individual level.

1. Baseline Findings

The key dependent variable of interest here is relative risk aversion. One potential caveat involves the estimation error of relative risk aversion because we estimate relative risk aversion by the product of absolute risk aversion and the per capita annual consumption of the city instead of the individual's annual consumption. Thus, the estimated slope coefficient of GDPGrowth might be *biased* when the dependent variable is relative risk aversion. To address this concern, we additionally use the natural logarithm of relative risk aversion as the dependent variable. When the ratio of the individual's consumption to the per capita consumption of the city is independent and identically distributed and fixed effects (individual fixed effects, city fixed effects, or time fixed effects) are controlled, the estimated slope coefficient of GDPGrowth is *unbiased*. See Internet Appendix IA.2 for details.

Table 5 reports the results of both regression models with the dependent variable being the raw estimated risk aversion and the natural logarithm of estimated risk aversion. Unless stated otherwise, all t-statistics in the panel regressions of the person-quarter panel are adjusted with standard errors clustered by both province and year×quarter and account for correlations across individuals, autocorrelations, and other correlations within the province. In Panel A, we control for the individual's person fixed effects. Similar to Pástor, Stambaugh, and Taylor (2017), the ordinary least squares estimator controlling for person fixed effects is a weighted average across individuals of the slope coefficients from person-to-person time-series regressions and thus reflects only the time-series variation in risk aversion and the GDP growth rate. It also absorbs the potential effect of time-invariant personal characteristics, such as demographics and wealth endowment, on risk aversion. In Column 1, the regression coefficient of GDPGrowth is -86.739, statistically significant with a t-statistic of -3.74, meaning that the individual's absolute risk aversion is negatively correlated with the GDP growth rate. When we use the natural logarithm of absolute risk aversion as the dependent variable in Column 2, the estimated coefficient is -13.602 with a t-statistic of -3.08. This means that a one-standard-deviation decline in the quarterly GDP growth rate is associated with a 24.5% increase in the individual's absolute risk aversion. For the individual's relative risk aversion, Column 4 shows it to be negatively correlated with the GDP growth rate with an estimated coefficient of -20.340 and statistically significant at the 1% level. The magnitude of the coefficient means that a one-standard-deviation decline in the quarterly GDP growth rate is associated with a 36.6% increase in relative risk aversion. The level regression in Column 3 is consistent: the estimated coefficient is -293.244, statistically significant at the 1% level, corresponding to an increase of 5.3 in relative risk aversion, though this level estimate is subject to the consumption-proxy bias. The results show that the time-series negative correlation between an individual's risk aversion and the GDP growth rate is both statistically and economically significant.

[INSERT TABLE 5 ABOUT HERE]

Panel B reports the results of panel regressions controlling for the province fixed effects. The regression coefficient essentially captures the average covariation in risk aversion and the GDP growth rate within the province. However, there is no cross-sectional variation in the GDP growth rate within the province, meaning that the regression coefficient captures the average time-series correlation between risk aversion and the GDP growth rate within the province. Therefore, controlling for province fixed effects could help verify the estimated time-series correlation of risk aversion and the GDP growth rate in Panel A. Columns 1 and 2 show that, consistent with the previous findings, the time-series correlation between the individual's absolute risk aversion and the

GDP growth rate within the province is significantly negative. The estimated coefficients of GDPGrowth are -68.413 and -15.210, which are statistically significant. When we use the raw relative risk aversion as the dependent variable in Column 3, the estimated coefficient is -242.217 with a t-statistic of -4.10. In Column 4, the estimated coefficient of GDPGrowth on the natural logarithm of relative risk aversion is -21.839 and statistically significant (t-statistic = -4.76). Considering the economic significance, Columns 2 and 4 show that, within the province, a one-standard-deviation decline in the quarterly GDP growth rate is associated with a 27.4% increase in the individual's absolute risk aversion and a 39.3% increase in relative risk aversion. In sum, the time-series negative correlation between the individual's risk aversion and the GDP growth rate within the province remains significant and is larger in economic magnitude.

The above shows the quantitatively negative relation between risk aversion and the GDP growth rate in the time series, providing direct support for time-varying and countercyclical risk aversion, which is the main empirical result of the paper. To further investigate the extent to which risk aversion varies inversely with economic trends, we estimate panel regressions controlling for both person and quarter fixed effects in Panel C. Compared with the panel regression controlling for the person fixed effects, the addition of time fixed effects would additionally control for the aggregate variation in variables over time but not the variation across individuals. Intuitively, the slope coefficient reflects the time-series relation of risk aversion and the GDP growth rate after deducting the aggregate economic trends effect. In Panel C, the estimated coefficients of GDPGrowth contract drastically in magnitude and are statistically indistinguishable from zero for both absolute risk aversion and relative risk aversion. This means that the time-series negative correlation between the individual's risk aversion and the GDP growth rate is almost entirely explained by changes in aggregate economic trends.

2. Evidence Against Mechanical Explanations

As discussed in Section II, the risk aversion formula in equation (5) maps each individual's deductible choice into an absolute risk aversion estimate through the expected-loss moments $E(L)$ and $E(L^2)$ and the premium rate p_i^0 (the price of the zero-deductible add-on, equal to 15% of the primary premium divided by coverage). This mapping raises the concern that the countercyclical pattern could be mechanically induced rather than reflecting genuine preference variation. First, if $E(L)$ or $E(L^2)$ varies cyclically (e.g., with road conditions or repair cost inflation) or geographically, the estimated risk aversion could inherit that variation. Second, because the add-on price is a fixed proportion of the base premium, any cyclical movement in premiums passes into p_i^0, and a higher p_i^0 mechanically implies a higher inferred r, so cyclical pricing could masquerade as countercyclical risk aversion. Third, the changing composition of insured vehicles over time could confound the relationship if vehicle age correlates with both pricing and the business cycle. We address all three concerns below: the first two by reestimating individual risk aversion via the Gibbs sampler under alternative inputs (Table 6) and the third by restricting the sample to narrow vehicle age bands (Table 7).

We first address the expected-loss concern. We replace the full-sample $E(L)$ and $E(L^2)$ with time- or geography-adjusted values and rerun the entire Gibbs sampling procedure from scratch. Specifically, we consider three specifications: (i) year-specific $E_t(L)$ and $E_t(L^2)$ computed from claims in each calendar year, (ii) year-quarter-specific $E_t(L)$ and $E_t(L^2)$ computed from claims in each quarter, and (iii) province-specific $E_p(L)$ and $E_p(L^2)$ computed from claims in each province. We then rerun the main GDP growth regressions from Table 5 using each set of reestimated measures. Panels A–C of Table 6 report the GDP growth coefficients, all controlling for person fixed effects. In Panel A (year-specific $E_t(L)$), Panel B (year-quarter-specific $E_t(L)$), and Panel C (province-specific $E_p(L)$), the coefficient on GDP growth is negative and statistically significant across all dependent variables.[7] Replacing the full-sample expected-loss moments with time- or geography-adjusted values therefore does not change the countercyclical pattern.

[INSERT TABLE 6 ABOUT HERE]

We next address the premium-rate concern with an experiment that removes any within-person time variation in the premium rate. We reestimate risk aversion via the full Gibbs sampler with each individual's premium rate p_i^0 held fixed at its first-policy value across all of the individual's policies. Panel D of Table 6 reports the results. The coefficient on GDP growth remains negative and statistically significant across all four risk aversion measures, indicating that the countercyclical pattern is unlikely to be mechanically driven by cyclical movements in the premium rate.[8] We caution that this is an illustrative experiment rather than a counterfactual reestimation: holding p_i^0 at a counterfactual value changes the price the individual faces, at which the optimal deductible choice could itself differ, yet we continue to treat the observed deductible choice as data.[9] This inconsistency biases the level of the reestimated risk aversion, so the exercise is best

[7] The coefficient magnitudes in Table 6 are larger than those in Table 5. Each alternative specification requires rerunning the Gibbs sampler from scratch with different $E(L)$ and $E(L^2)$ inputs, which changes both the premium-to-expected-loss ratio and the expected loss differential. Because these inputs enter the likelihood, the posterior distribution of claim rates λ_i shifts, producing individual posterior means with somewhat greater cross-sectional and temporal variation. The relevant comparison across specifications is the sign and statistical significance of the GDP growth coefficient—both uniformly preserved—not the coefficient magnitude, which depends on the scale and dispersion of the risk aversion measure.

[8] As further evidence that cyclical pricing does not drive the result, we exploit the staggered rollout of the China Insurance Regulatory Commission (CIRC) auto insurance pricing reform (2015–2016) in a difference-in-differences design. The reform was introduced across provinces in three waves (six pilot jurisdictions on June 1, 2015; 12 more on January 1, 2016; and the remaining 18 by July 1, 2016) (Zheng, Yao, Shi, Deng, and Zheng (2022)). Regressing the premium rate on treatment-wave × post-reform interactions, with person and jurisdiction fixed effects, the estimated effects on the premium rate are essentially zero across all three waves (t-statistics of −0.79, −0.66, and −1.23 without year×quarter fixed effects, and −0.57, −0.11, and −0.90 with them; see Internet Appendix Table IA.II). The reform thus did not mechanically shift the add-on price p_i^0 that enters equation (5), consistent with Zheng et al. (2022), who find that the reform redistributed premiums across risk types rather than shifting their level—opposing cross-sectional effects that cancel at the individual level once person fixed effects are included.

[9] Our estimation recovers (r_i, λ_i) from each individual's observed deductible choice and realized claims; it infers

interpreted as a diagnostic of whether the countercyclical pattern survives when the premium rate is held fixed, not as a structurally interpretable estimate of its magnitude.

We finally consider the concern that vehicle composition changes over time: if newer vehicles carry systematically different pricing or deductible choices, shifts in the vehicle age distribution could confound the relationship between risk aversion and macroeconomic conditions. We therefore restrict the sample to narrow car age bands—vehicles aged 1–3, 4–6, and 7–9 years—and reestimate the main specification within each band, holding vehicle age approximately constant. Table 7 reports the results. The countercyclical pattern persists across all three bands and strengthens for older vehicles: the coefficient on Ln(RRA) rises in magnitude to −42.628 ($t = -2.60$) in the 7- to 9-year band. If the pattern were driven by mechanical coverage dynamics, the effect should be weaker for older cars, which have lower replacement values; the opposite gradient is more consistent with genuine preference variation.

[INSERT TABLE 7 ABOUT HERE]

Taken together, these analyses provide evidence against the most plausible mechanical explanations for the countercyclical pattern—cyclical loss moments, premium-rate movements, and vehicle composition. We nonetheless emphasize a limitation of our design. As Panel C of Table 5 shows, the GDPGrowth coefficient becomes statistically indistinguishable from zero once common year×quarter fixed effects are included, so identification ultimately rests on aggregate time-series variation. As a result, we cannot fully rule out other market-wide changes, such as underwriting, contract menus, or sales practices, that coincide with the business cycle and could affect the insurance-implied risk aversion measure. We view such confounds as unlikely to reproduce the

preferences from observed behavior rather than generating behavior from primitives, so it cannot be reevaluated at counterfactual inputs.

breadth of patterns we document, but the present design cannot eliminate them entirely.

3. Robustness Checks

We subject the baseline countercyclical relationship to a battery of additional robustness checks, integrated below one by one. For brevity, the corresponding tables are collected in the Internet Appendix.

In the aggregate-level analysis, the variation in individuals' risk aversion lags behind macroeconomic indicators. To investigate this lag reaction at the individual level, we estimate panel regressions of risk aversion on the lagged GDP growth rate. Internet Appendix Table IA.III reveals two noteworthy findings. First, the lag reaction effect indeed exists in the time series, at least when the duration of the lag is shorter than one year: the slope coefficients of lagged GDPGrowth remain economically and statistically significant for both absolute and relative risk aversion when the lag duration ranges from one quarter to four quarters. Second, the lagged reaction decays as the lag lengthens. Focusing on the relative risk aversion measure, the slope coefficient of lagged GDPGrowth decreases monotonically in magnitude from −289.822 to −259.327 for the raw measure and from −20.062 to −18.648 for its natural logarithm as the lag duration lengthens from one to four quarters, with a similar but more slowly decaying pattern for absolute risk aversion.

We next examine first differences. Internet Appendix Table IA.IV reports regressions of the change in risk aversion on GDP growth. Under person fixed effects (Panel A), the coefficient of GDPGrowth is −64.686 on the change in absolute risk aversion and −184.841 on the change in relative risk aversion, both significant at the 5% level; the estimates are slightly smaller but remain significant under province fixed effects (Panel B), and—as in the baseline—become indistinguishable from zero once both person and time fixed effects are included.

We then replace the GDP growth rate with alternative macroeconomic indicators. Internet Appendix Table IA.V reports the individual-level time-series regressions. In Panel A, risk aversion is negatively correlated with the industrial production cycle: the coefficient of IndGrowth is −7.437 for Ln(RRA) and −4.660 for Ln(ARA), and both are statistically significant at the 5% and 10% levels. In Panel B, using the growth rate of retail sales, the coefficients of RetailGrowth (−10.794 and −6.534 for Ln(RRA) and Ln(ARA)) are also statistically significant. In Panel C, the coefficients of REstateGrowth are −1.690 for Ln(RRA) and −0.950 for Ln(ARA). The magnitudes imply that a one-standard-deviation decrease in the growth of industrial production, retail sales, and real estate investment is associated with a 26.8%, 25.9%, and 19.6% increase in relative risk aversion, respectively. The pattern also holds for per capita consumption growth, the variable at the center of the Campbell and Cochrane (1999) habit-formation model, in which risk aversion rises as consumption falls toward an external habit level. Relating risk aversion to the annual growth of per capita consumption within the province (Internet Appendix Table IA.VI), the coefficient is −25.985 for raw absolute risk aversion and −4.133 for its logarithm, and −78.341 and −5.060 for raw and log relative risk aversion, all statistically significant; a one-standard-deviation decrease in consumption growth is associated with a 14.9% increase in absolute and an 18.2% increase in relative risk aversion.

Whereas our baseline uses province-level GDP growth, we next exploit finer geographic variation.[10] Across all cities, the estimated coefficients of the annual GDP growth rate are significantly negative under both person and city fixed effects, with a 1% decrease in annual GDP growth associated with roughly a 12% increase in absolute and a 17% increase in relative risk

[10]There are 295 cities and nearly 10,000 applicants per city on average, but quarterly city-level GDP growth is not systematically available, so we use annual growth for all cities and quarterly growth for the provincial capitals.

aversion (Internet Appendix Table IA.VII). For the provincial capitals, the quarterly regressions likewise show a negative relation, though smaller in magnitude (-11.720 for Ln(ARA) and -17.175 for Ln(RRA)) than in the all-province sample (Internet Appendix Table IA.VIII).

We also test the relationship at the province-quarter level, averaging risk aversion across individuals within each province. Aggregation removes cross-individual correlation and attenuates individual-level imprecision. As Internet Appendix Table IA.IX shows, the average risk aversion measure is negatively and significantly related to the quarterly growth rates of aggregate GDP, retail sales, industrial production, and real estate investment, all at the 1% level, though with smaller magnitudes than the individual-level regressions.

We next check whether the time-series covariation could be an artifact of changing sample composition by estimating panel regressions among individuals who continue to buy auto insurance every year.[11] This estimate addresses several concerns: the entry and exit of drivers with different risk aversion can move the aggregate measure; the estimator with person fixed effects places larger weight on individuals with more observations when the panel is unbalanced (Pástor et al. (2017)); and a longer per-individual sample better captures the cyclical covariation. Internet Appendix Table IA.X reports the results. In the quasi-balanced sample, the evidence is statistically significant and economically stronger: the coefficient of GDPGrowth is -370.956 on raw relative risk aversion and -24.523 on its logarithm, both significant at the 1% level and larger than the full-sample estimates, with similar results for absolute risk aversion. The person- and province-fixed-effects estimates are also very close in this sample.

Finally, our inference is robust to the choice of standard-error clustering. Because residuals

[11] In the person-quarter panel, ideally we would keep only individuals who buy auto insurance each quarter to obtain a perfectly balanced panel. However, this restriction would limit the sample to a very small group of rich applicants and would not be representative; we therefore keep individuals who buy auto insurance every year to obtain a quasi-balanced panel.

may be correlated across individuals and over time (Petersen (2009)), we report t-statistics with standard errors clustered by both province and quarter in the person-quarter panel regressions. Internet Appendix Table IA.XI compares alternative clustering schemes: clustering by province or by quarter produces much larger standard errors than clustering by person, and two-way clustering by province and quarter yields the most conservative standard errors. The statistical significance of the GDPGrowth coefficient is preserved throughout.

Across these specifications, the negative time-series relationship between risk aversion and macroeconomic conditions is preserved, reinforcing that individuals' risk aversion is time varying and countercyclical. The exception is Panel C of the city-level regressions, where calendar-time fixed effects absorb the aggregate time-series variation on which our identification rests.

V. Psychological Sources of Risk Aversion

In theory, psychological forces could also relate to individuals' risk preferences and thus to changes in risk aversion. Existing empirical studies find that the emotion of fear may be related to individuals' risk-taking behavior and may contribute to countercyclical risk aversion (Lerner and Keltner (2001), Cohn et al. (2015)). In addition, seasonal mood swings, formally known as SAD or "winter blues," can lead to seasonal variation in risk aversion, resulting in seasonal changes in returns and investing behaviors (Kamstra et al. (2003), Kamstra, Kramer, and Levi (2015), Garrett, Kamstra, and Kramer (2005), Kamstra, Kramer, Levi, and Wermers (2017)). Another feature of psychology—superstition—could also have material consequences for individuals' risk-taking behavior (Fisman et al. (2023)). Lastly, we also examine calendar events such as holidays, fiscal year-ends, and bonus seasons.

A. Seasonality in Risk Aversion

The link between seasons and risk aversion is based on the view that a seasonal reduction in daylight hours can lead to a marked deterioration in people's moods and is also based on clinical evidence that a dampened mood can have a negative influence on risk-taking behavior (Kamstra et al. (2017)). The incidence of depression is linked with SAD because of the seasonal reduction in daylight hours. In addition, healthy people could also suffer a milder but still problematic disorder, commonly called "winter blues" (Kamstra et al. (2003), Kramer and Weber (2012)). Existing studies have documented seasonal patterns in the returns of stocks and bonds, the movement of money between mutual fund categories, both consistent with seasonally varying risk preferences (Kamstra et al. (2003), Kamstra et al. (2015), Garrett et al. (2005), Kamstra et al. (2017)). Kamstra, Kramer, Levi, and Wang (2014) also developed an asset pricing model with a representative agent experiencing seasonally varying risk preferences and generated the empirically observed seasonal patterns in equity and Treasury returns.

In this section, we examine seasonality in risk aversion with our measures. We follow Kamstra et al. (2003) to measure the effect of SAD by the number of nighttime hours from sunset to sunrise during the fall and winter. We first calculate the sun's declination angle at day t as $\lambda_t = 0.4102 \times sin(\frac{2\pi}{365} \times (Julian_t - 80.25))$, where $Julian_t$ is the number of the day in the year, which ranges from 1 to 365 (366 in a leap year). Since all cities in our sample are in the Northern Hemisphere, we then calculate the number of nighttime hours as $SAD_t = 12 - 7.72 \times arccos(-tan(\frac{2\pi\delta}{360})tan(\lambda_t))$, where δ is the latitude of the city in which the applicant lives. The SAD_t measure is set to be zero in the spring and summer. We also include a dummy variable for the fall and winter. The results are reported in Table 8. City and year fixed effects are included in all specifications to control for the variations in risk aversion across cities and years.

[INSERT TABLE 8 ABOUT HERE]

In Panel A, Column 1 shows that absolute risk aversion appears to be positively correlated with the SAD measure with a coefficient of 0.336, which is statistically significant with a t-statistic of 3.59. In Column 2, the indicator variable of fall and winter is statistically significant with a coefficient of 0.474 and a t-statistic of 4.53. We jointly estimate a regression of absolute risk aversion on the SAD measure and the indicator variable of fall and winter in Column 3; both coefficients decrease in magnitude but remain statistically significant. When we use the natural logarithm of absolute risk aversion as the dependent variable in Columns 4 to 6, the results also show a positive correlation between absolute risk aversion and the SAD measure and indicate that individuals' absolute risk aversion is statistically higher in the fall and winter. We then reestimate the regression of relative risk aversion in Panel B. In Columns 1 and 2, the coefficient of SAD is 0.769 and the coefficient of the indicator variable of fall and winter is 1.072 in the univariate regression, and both are statistically significant. We interpret the economic magnitudes in the multivariate regression in Column 3 as follows. First, the SAD measure is significant with a coefficient of 0.643 and a t-statistic of 2.11, meaning that a one-hour increase in nighttime hours in the fall and winter is associated with an increase in the relative risk aversion coefficient of 0.643. Second, the coefficient of the indicator variable of fall and winter is 0.259, remaining significant. Since the mean of the SAD measure in the fall and winter is 1.264, an average individual's relative risk aversion is 1.072 ($0.259 + 1.264 \times 0.643$) higher in the fall and winter than in the spring and summer. This magnitude is the same as the coefficient in the univariate regression in Column 2. In

Columns 4 to 6, the correlations of both the SAD measure and the indicator variable of fall and winter with individuals' relative risk aversion are also positive and statistically significant, consistent with the results of level regressions. Overall, the results are consistent with individuals' risk aversion increasing with the length of the night and being higher in the fall and winter.

B. Zodiac Years

We follow Fisman et al. (2023) to investigate the role of superstition, specifically the "zodiac year effect," in the variation in risk aversion. In China, the zodiac year is the year when each person's age is a multiple of 12. The zodiac year effect refers to the superstitious belief that people are at risk of encountering misfortunes in the zodiac year and therefore are more cautious when making decisions under uncertainty. To gain some insight into the plausibility of individuals' superstition affecting their level of risk aversion, we test the risk aversion fluctuations around the zodiac year.

In Table 9, we estimate panel regressions of risk aversion measures on the zodiac year indicator, controlling for demographic variables and car attributes. Odd-numbered columns include year fixed effects, and even-numbered columns add person fixed effects to exploit within-individual variation in zodiac year status. In the year fixed effects regressions, we find that individuals who are in their zodiac year have a 1.5% higher level of absolute risk aversion and a 1.6% higher level of relative risk aversion than others, and both coefficients are statistically significant after controlling for demographic variables and car attributes. With person and year fixed effects, the zodiac year effect remains positive and statistically significant for log risk aversion measures. The zodiac year is associated with a 0.5% higher Ln(ARA) (t-statistic = 4.58) and a 0.4% higher Ln(RRA) (t-statistic = 4.61), consistent with the zodiac year effect reflecting within-individual variation rather than cross-sectional composition effects. These results support the hypothesis that psychological forces could lead to time-varying risk aversion; in this case, an individual's level of risk aversion is higher in the zodiac year every 12 years, consistent with superstitious beliefs.

[INSERT TABLE 9 ABOUT HERE]

C. Risk Aversion around Calendar Events

Stock returns on trading days before holidays are abnormally high: 9–14 times higher than ordinary-day returns across US exchanges and international markets (Ariel (1990), Kim and Park (1994)), and the pattern persists over 90 years of data (Lakonishok and Smidt (1988)). The leading explanation is that the anticipation of leisure and festivity elevates mood, which in turn shifts risk attitudes (Meier (2022)). Our individual-level risk aversion measures allow us to examine this channel by tracing how risk preferences vary around calendar events.

We conduct event studies around China's major national holidays: National Day (October 1–7, a week-long "Golden Week" of collective celebration and mass travel), Workers' Day (May 1, leisure and public festivities), Spring Festival (Chinese New Year, a seven-day holiday that coincides with the bonus season), and New Year's Day (January 1, coinciding with the fiscal year-end). We restrict the sample to policies issued within one week before each event, during the event, and one week after, and estimate panel regressions of risk aversion on indicators for the event period (*Event*) and the post-event week (*Post1w*), with the pre-event week as the benchmark. All regressions include person and year fixed effects.

Table 10 reports the results. When we pool four holidays (Columns 1–4), the log risk aversion measures are significantly higher during the holiday period: Ln(ARA) increases by 0.066

(t = 3.06) and Ln(RRA) by 0.060 (t = 2.80) relative to the pre-holiday week. The effect persists into the post-holiday week, with coefficients of 0.034 (t = 2.55) for Ln(ARA) and 0.035 (t = 2.70) for Ln(RRA), suggesting that the holiday effect does not disappear immediately.[12] When we examine two holidays that coincide with fiscal year-ends and bonus seasons, New Year's Day (Columns 5–8) shows no significant effect on any measure of risk aversion, and Spring Festival (Columns 9–12) is similarly not statistically significant.[13]

[INSERT TABLE 10 ABOUT HERE]

These associations are consistent with a mood and affect channel: National Day and Workers' Day—holidays centered on collective celebration and routine disruption—are associated with elevated risk aversion, much as seasonal darkness is associated with mood and risk preferences in the SAD analysis of Section V.A.

Together with the zodiac year finding in Section V.B, these analyses are consistent with psychological forces—seasonal mood, culturally embedded beliefs, and holiday-related emotional states—correlating with individual risk aversion over time.

[12] In the level specifications, by contrast, the point estimates carry the opposite (negative) sign—marginally significant for pooled-holiday RRA (t = −1.91) and insignificant elsewhere. We emphasize the log specifications here, as throughout the paper. For relative risk aversion this is a matter of bias: because we proxy each individual's consumption with city-level per capita consumption, the raw level is biased, whereas its logarithm is unbiased once fixed effects absorb the (assumed i.i.d.) proxy error, as discussed in Section IV.B.1 and derived in Internet Appendix IA.2. Absolute risk aversion involves no such proxy and is unbiased in both levels and logs; there we prefer the log because the risk aversion distribution is highly right-skewed, so the level regression is sensitive to a small number of extreme values while the log is robust to them.

[13] We also examined National Day and Workers' Day separately and in combination. The event effects are concentrated in these two holidays.

VI. Conclusions

A central question in the asset pricing literature is whether individuals' risk aversion is time varying and countercyclical. Despite its theoretical importance, this question lacks a clear empirical answer. In this paper, we estimate individuals' risk aversion from data on deductible choices in auto insurance contracts, which are designed to help individuals hedge against risk. The availability of detailed, nationwide auto insurance data make it possible to investigate the time-series variation in risk aversion. We find that our risk aversion estimates are of the same order of magnitude as similar estimators in the literature. Individuals with higher levels of risk aversion are less likely to buy lotteries and stocks but more likely to buy insurance and bonds. We provide empirical evidence that risk aversion is time varying and countercyclical at both the aggregate level (indicatively) and the individual level (robustly with individual fixed effects). A one-standard-deviation decline in the quarterly GDP growth rate is associated with a 36.6% increase in relative risk aversion. Beyond the business cycle, risk aversion is also associated with psychological factors: it is higher during the long nights of fall and winter, in individuals' zodiac years, and around major national holidays.

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Table 1. Summary Statistics

This table reports the summary statistics. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. Male equals one for male applicants and zero for female applicants. Age is the age of applicants. LnExpense is the log of the policy premium. LnCoverage is the log of the policy coverage. CarAge is the age of the vehicle. GDPGrowth is the real quarterly GDP growth rate of each province. IndGrowth is the quarterly growth rate of industrial production in each province. RetailGrowth is the quarterly growth rate of aggregate retail sales in each province. REstateGrowth is the quarterly growth rate of real estate investments in each province. ConsGrowth is the annual growth rate of per capita consumption in each province. The macro indicators are from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

Variable	N	Mean	Std	p1	p25	Median	p75	p99
ARA ($\times 10^{-4}$)	10,229,255	6.842	9.141	0.000	1.655	3.748	7.948	54.289
Ln(ARA)	10,229,255	-8.259	2.297	-18.424	-8.706	-7.889	-7.137	-5.216
RRA	8,997,276	15.112	22.116	0.000	3.412	7.818	16.776	139.872
Ln(RRA)	8,997,276	1.686	2.334	-8.651	1.227	2.056	2.820	4.941
Male	10,229,255	0.723	0.447	0	0	1	1	1
Age	10,229,255	38.292	9.289	22	31	38	45	62
LnExpense	10,229,255	7.225	0.479	6.188	6.892	7.178	7.532	8.534
LnCoverage	10,229,255	11.452	0.584	10.032	11.076	11.449	11.826	12.885
CarAge	10,229,255	2.914	2.412	0	1	2	4	10
GDPGrowth	10,229,255	0.087	0.018	0.040	0.076	0.083	0.095	0.147
IndGrowth	9,649,944	0.090	0.036	0.003	0.071	0.083	0.110	0.211
RetailGrowth	9,649,944	0.119	0.024	0.055	0.106	0.119	0.129	0.180
REstateGrowth	9,646,529	0.124	0.116	-0.173	0.050	0.110	0.180	0.473
ConsGrowth	9,649,944	0.084	0.036	-0.011	0.059	0.079	0.097	0.188

Table 2. Regressions of Risk Aversion on Demographic Characteristics

This table reports the panel regressions of risk aversion on demographic characteristics. The absolute risk aversion (ARA) of each applicant in each year is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. Male equals one for male applicants and zero for female applicants. Age is the age of applicants. LnExpense is the log of the policy premium. LnCoverage is the log of the policy coverage. CarAge is the age of the vehicle. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4	5	6	7	8
	ARA		Ln(ARA)		RRA		Ln(RRA)	
Male	0.384***	0.394***	0.006	0.013	0.713***	0.790***	-0.010	0.002
	(6.82)	(7.24)	(0.60)	(1.59)	(4.19)	(4.69)	(-0.74)	(0.17)
Age	0.101***	0.102***	0.014***	0.014***	0.200***	0.208***	0.011***	0.012***
	(17.65)	(17.64)	(16.51)	(17.20)	(11.56)	(12.24)	(11.00)	(12.37)
LnExpense	7.227***	7.307***	0.634***	0.642***	17.113***	17.275***	0.523***	0.520***
	(13.90)	(13.95)	(6.75)	(11.03)	(9.21)	(9.20)	(5.53)	(8.68)
LnCoverage	-16.924***	-16.838***	-2.578***	-2.479***	-38.480***	-37.759***	-2.484***	-2.349***
	(-19.21)	(-17.97)	(-30.72)	(-42.62)	(-12.47)	(-11.79)	(-30.79)	(-42.56)
CarAge	-0.018	-0.072**	-0.098***	-0.138***	0.740***	0.399***	-0.064***	-0.118***
	(-0.73)	(-2.18)	(-9.18)	(-12.33)	(6.24)	(3.29)	(-5.38)	(-10.09)
Constant	144.358***	142.897***	16.444***	15.332***	322.203***	313.388***	26.169***	24.740***
	(19.88)	(19.15)	(34.98)	(50.42)	(13.19)	(12.89)	(51.04)	(82.40)
Fixed Effect	No	Year×Quarter	No	Year×Quarter	No	Year×Quarter	No	Year×Quarter
Obs	10,229,255	10,229,255	10,229,255	10,229,255	8,997,276	8,997,276	8,997,276	8,997,276
Within R^2	0.635	0.612	0.283	0.259	0.578	0.541	0.270	0.240

Table 3. Risk Aversion and Risky Asset Preference

This table reports the correlations between the average risk aversion and aggregate risky asset preference. The regressions in Columns 1 to 4 are on the province-quarter panel, and the regressions in Columns 5 to 8 are on the province-year panel. ΔLn(Lottery) is the log change of current lottery sales to the four-quarter-prior lottery sales within the province. Lottery sales are the sum of welfare lottery sales and sports lottery sales. ΔLn(Insurance) is the log change of current total insurance sales to the four-quarter-prior insurance sales within the province, including the sales of property insurance, life insurance, accident insurance, and health insurance. RelStock is relative stock trading, which is defined as the ratio of annual stock trading volume to the total trading volume of stocks, funds, bonds, and warrants. RelBond is relative bond trading, which is defined as the ratio of annual bond trading volume to the total trading volume of stocks, funds, bonds, and warrants. The independent variable is the average absolute risk aversion (ARA) or average relative risk aversion (RRA) of applicants in the province, or the logarithm thereof. The absolute risk aversion of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. We average ARA and RRA across the applicants in each province. We control for province fixed effects in all specifications. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors two-way clustered by province and year×quarter in Columns 1 to 4, and by province and year in Columns 5 to 8. The sample is from the first quarter of 2011 to the fourth quarter of 2017 for the province-quarter panel and from 2011 to 2017 for the province-year panel.

	1	2	3	4	5	6	7	8
	ΔLn(Lottery)		ΔLn(Insurance)		RelStock		RelBond	
ARA	-0.023***		0.017***		-0.028**		0.026**	
	(-4.53)		(3.99)		(-2.81)		(2.50)	
RRA		-0.009***		0.007***		-0.009**		0.009**
		(-4.81)		(4.33)		(-2.80)		(2.57)
Fixed Effect	Prov	Prov	Prov	Prov	Prov	Prov	Prov	Prov
Obs	812	811	812	811	202	202	196	196
Within R^2	0.122	0.148	0.153	0.209	0.217	0.225	0.183	0.195
	ΔLn(Lottery)		ΔLn(Insurance)		RelStock		RelBond	
Ln(ARA)	-0.169***		0.124***		-0.196**		0.184*	
	(-4.61)		(4.07)		(-2.68)		(2.42)	
Ln(RRA)		-0.140***		0.111***		-0.142*		0.129*
		(-5.26)		(4.87)		(-2.43)		(2.18)
Fixed Effect	Prov	Prov	Prov	Prov	Prov	Prov	Prov	Prov
Obs	812	811	812	811	202	202	196	196
Within R^2	0.126	0.173	0.159	0.253	0.205	0.217	0.176	0.179

Table 4. Factor Return Predictability

This table reports monthly predictive regressions of Chinese equity factor returns on lagged aggregate risk aversion. The dependent variable is the one-month-ahead factor return. The factors are the market return, the market premium, small-minus-big (SMB), high-minus-low (HML), robust-minus-weak (RMW), and conservative-minus-aggressive (CMA). ARA (RRA) is the cross-sectional average of absolute (relative) risk aversion across all individuals in a given month. Ln(ARA) and Ln(RRA) are the log counterparts. The sample consists of 84 monthly observations from January 2011 to December 2017. Reported in parentheses are t-statistics based on heteroskedasticity-robust standard errors.

	1	2	3	4	5	6	7	8	9	10	11	12
	Market Return		Market Premium		SMB		HML		RMW		CMA	
ARA	-0.035		0.105		-0.554***		0.254*		0.309***		-0.059	
	(-0.18)		(0.57)		(-3.23)		(1.86)		(2.67)		(-0.66)	
RRA		-0.000		0.041		-0.163***		0.075*		0.092**		-0.018
		(-0.00)		(0.77)		(-3.28)		(1.85)		(2.60)		(-0.67)
Constant	0.992	0.759	-0.116	-0.012	4.556***	3.247***	-1.488	-0.893	-2.390**	-1.674**	0.707	0.577
	(0.53)	(0.53)	(-0.07)	(-0.01)	(3.00)	(2.92)	(-1.30)	(-1.08)	(-2.63)	(-2.52)	(1.16)	(1.37)
Obs	84	84	84	84	84	84	84	84	84	84	84	84

	Market Return		Market Premium		SMB		HML		RMW		CMA	
Ln(ARA)	-0.276		0.804		-4.188***		1.870*		2.378**		-0.467	
	(-0.18)		(0.55)		(-3.00)		(1.71)		(2.61)		(-0.66)	
Ln(RRA)		0.165		0.838		-2.578***		1.197*		1.506**		-0.248
		(0.16)		(0.89)		(-2.87)		(1.68)		(2.42)		(-0.51)
Constant	-1.275	0.336	6.509	-1.563	-30.011***	7.462***	13.988*	-2.861	17.197**	-4.188**	-3.130	0.948
	(-0.12)	(0.11)	(0.63)	(-0.55)	(-3.00)	(2.89)	(1.77)	(-1.44)	(2.59)	(-2.48)	(-0.60)	(0.78)
Obs	84	84	84	84	84	84	84	84	84	84	84	84

Table 5. Regressions of Risk Aversion on GDP Growth Rate

This table reports the panel regressions of risk aversion on the real quarterly GDP growth rate. Panel A reports the panel regressions controlling for the person fixed effects. Panel B reports the panel regressions controlling for the province fixed effects. Panel C reports the panel regressions controlling for both person and year×quarter fixed effects. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real quarterly GDP growth rate of each province from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Person Fixed Effect				
GDPGrowth	-86.739***	-13.602***	-293.244***	-20.340***
	(-3.74)	(-3.08)	(-3.89)	(-3.93)
Fixed Effect	Person	Person	Person	Person
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.048	0.011	0.068	0.023
Panel B. Province Fixed Effect				
GDPGrowth	-68.413***	-15.210***	-242.217***	-21.839***
	(-3.79)	(-3.82)	(-4.10)	(-4.76)
Fixed Effect	Prov	Prov	Prov	Prov
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.013	0.010	0.026	0.019
Panel C. Person and Year×Quarter Fixed Effects				
GDPGrowth	-15.154	0.876	-25.950	1.507
	(-1.48)	(0.24)	(-0.62)	(0.38)
Fixed Effect	Person, Year×Quarter	Person, Year×Quarter	Person, Year×Quarter	Person, Year×Quarter
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.001	0.000	0.000	0.000

Table 6. Risk Aversion on GDP Growth Rate: Evidence Against Mechanical Explanations

This table reports regressions of risk aversion on the GDP growth rate, where risk aversion is reestimated via Gibbs sampling under alternative specifications. Panels A–C replace the full-sample $E(L)$ and $E(L^2)$ with year-specific $E_t(L)$ (Panel A), year-quarter-specific $E_t(L)$ (Panel B), and province-specific $E_p(L)$ (Panel C). Panel D instead holds each individual's premium rate p_i^0 fixed at the individual's first-policy value to remove within-person time variation in the premium rate. All specifications control for person fixed effects. All variables are winsorized at the 1% and 99% level. The relative risk aversion (RRA) is the product of absolute risk aversion (ARA) and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real quarterly GDP growth rate of each province from the National Bureau of Statistics. Reported in parentheses are t-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Year-Specific $E_t(L)$ and $E(L^2)$				
GDPGrowth	-223.047^{***}	-22.393^{***}	-661.841^{***}	-28.557^{***}
	(−4.53)	(−2.78)	(−4.07)	(−3.44)
Fixed Effect	Person	Person	Person	Person
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.038	0.005	0.044	0.008
Panel B. Year-Quarter-Specific $E_t(L)$ and $E(L^2)$				
GDPGrowth	-298.789^{***}	-29.957^{***}	-877.869^{***}	-36.848^{***}
	(−3.61)	(−3.16)	(−3.36)	(−3.71)
Fixed Effect	Person	Person	Person	Person
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.042	0.009	0.047	0.013
Panel C. Province-Specific $E_p(L)$ and $E(L^2)$				
GDPGrowth	-449.655^{***}	-65.928^{***}	$-1{,}317.626^{***}$	-72.770^{***}
	(−3.88)	(−6.03)	(−3.45)	(−5.81)
Fixed Effect	Person	Person	Person	Person
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.061	0.047	0.062	0.053
Panel D. First-Policy Premium Rate (Year-Specific $E_t(L)$)				
GDPGrowth	-124.527^{***}	-33.301^{***}	-383.223^{***}	-39.769^{***}
	(−7.65)	(−7.00)	(−5.93)	(−7.82)
Fixed Effect	Person	Person	Person	Person
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.050	0.019	0.068	0.025

Table 7. Countercyclical Risk Aversion across Narrow Car Age Bands

This table reports regressions of risk aversion on the GDP growth rate for subsamples restricted to narrow car age bands. Panel A restricts to vehicles aged 1–3 years, Panel B to 4–6 years, and Panel C to 7–9 years. All specifications control for person fixed effects. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real quarterly GDP growth rate of each province from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors two-way clustered by province and year×quarter.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Car Aged 1–3 Years				
GDPGrowth	−5.431	−3.556	-66.281^{***}	-8.456^{***}
	(−0.81)	(−1.26)	(−2.74)	(−2.68)
Fixed Effect	Person	Person	Person	Person
Obs	3,015,747	3,015,747	2,546,646	2,546,646
Within R^2	0.000	0.000	0.011	0.002
Panel B. Car Aged 4–6 Years				
GDPGrowth	-51.636^{*}	-14.430^{**}	-211.553^{**}	-21.365^{***}
	(−1.82)	(−2.14)	(−2.38)	(−2.78)
Fixed Effect	Person	Person	Person	Person
Obs	1,180,650	1,180,650	1,036,650	1,036,650
Within R^2	0.011	0.006	0.024	0.011
Panel C. Car Aged 7–9 Years				
GDPGrowth	-186.427^{*}	-30.955^{**}	-681.361^{**}	-42.628^{***}
	(−1.79)	(−2.05)	(−2.15)	(−2.60)
Fixed Effect	Person	Person	Person	Person
Obs	283,455	283,455	256,914	256,914
Within R^2	0.026	0.018	0.044	0.029

Table 8. Seasonally Varying Risk Aversion

This table reports regression results of individuals' risk aversion on the seasonal affective disorder measure. The absolute risk aversion (ARA) of each applicant in each quarter is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of the absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. We follow Kamstra et al. (2003) to construct a measure (SAD) to capture the effects of seasonal affective disorder by the length of the night during the fall and winter. Specifically, we first calculate the sun's declination angle in day t as $\lambda_t = 0.4102 \times \sin(\frac{2\pi}{365} \times (Julian_t - 80.25))$, where Julian$_t$ is the number of the day in the year, which ranges from 1 to 365 (366 in a leap year). Then we calculate the number of nighttime hours as $SAD_t = 12 - 7.72 \times \arccos(-\tan(\frac{2\pi\delta}{360})\tan(\lambda_t))$, where δ is the latitude of the city in which the applicant lives. SAD_t is set to be zero in the spring and summer. Fall/Winter is a dummy variable that equals one in the fall and winter and zero otherwise. Spring is from March 21 to June 20, summer is from June 21 to September 20, fall is from September 21 to December 20, and winter is from December 21 to March 20. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors two-way clustered by city and year in all specifications. The sample is from 2011 to 2017.

Panel A. Absolute Risk Aversion

	1	2	3	4	5	6
	ARA			Ln(ARA)		
SAD	0.336***		0.271**	0.061***		0.052**
	(3.59)		(2.47)	(3.25)		(2.56)
Fall/Winter		0.474***	0.132***		0.085***	0.020***
		(4.53)	(3.42)		(3.71)	(3.04)
Fixed Effect	City,Year	City,Year	City,Year	City,Year	City,Year	City,Year
Obs	10,166,390	10,166,390	10,166,390	10,166,390	10,166,390	10,166,390
Within R^2	0.062	0.061	0.062	0.048	0.048	0.048

Panel B. Relative Risk Aversion

	RRA			Ln(RRA)		
SAD	0.769***		0.643**	0.062***		0.053**
	(2.89)		(2.11)	(3.07)		(2.40)
Fall/Winter		1.072***	0.259***		0.086***	0.018**
		(3.53)	(2.79)		(3.53)	(2.42)
Fixed Effect	City,Year	City,Year	City,Year	City,Year	City,Year	City,Year
Obs	8,997,276	8,997,276	8,997,276	8,997,276	8,997,276	8,997,276
Within R^2	0.100	0.100	0.100	0.067	0.067	0.067

Table 9. Risk Aversion in Zodiac Years

This table reports the panel regressions of risk aversion on the zodiac year indicator. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. Zodiac is an indicator variable equal to one when the applicant's age is a multiple of 12 and zero otherwise. Male equals one for male applicants and zero for female applicants. Age is the age of applicants. LnExpense is the log of the policy premium. LnCoverage is the log of the policy coverage. CarAge is the age of the vehicle. Odd-numbered columns control for year fixed effects. Even-numbered columns control for both person and year fixed effects, exploiting within-individual variation in zodiac year status. Male is absorbed by the person fixed effects and therefore omitted in the even-numbered columns. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by province and year in all specifications. The sample is from 2011 to 2017.

	1	2	3	4	5	6	7	8
	ARA		Ln(ARA)		RRA		Ln(RRA)	
Zodiac	0.119**	0.085**	0.015***	0.005***	0.318**	0.260**	0.016**	0.004***
	(3.22)	(3.29)	(4.40)	(4.58)	(2.49)	(2.73)	(3.68)	(4.61)
Male	0.399***		0.013		0.795***		0.002	
	(5.46)		(1.41)		(3.77)		(0.15)	
Age	0.102***	0.266***	0.014***	0.007	0.207***	0.617***	0.012***	-0.000
	(11.21)	(5.07)	(16.25)	(0.55)	(7.30)	(3.99)	(12.51)	(-0.02)
LnExpense	7.335***	3.298***	0.654***	0.663***	17.349***	8.787***	0.539***	0.634***
	(10.56)	(7.22)	(9.57)	(5.70)	(6.95)	(8.55)	(7.88)	(5.38)
LnCoverage	-16.875***	-20.305***	-2.498***	-2.962***	-37.815***	-51.823***	-2.374***	-2.975***
	(-10.22)	(-19.38)	(-35.27)	(-15.47)	(-6.98)	(-13.66)	(-34.66)	(-15.92)
CarAge	-0.073*	-1.900***	-0.138***	-0.152***	0.404*	-5.234***	-0.118***	-0.151***
	(-2.43)	(-5.73)	(-9.50)	(-8.49)	(2.19)	(-5.08)	(-7.25)	(-9.11)
Fixed Effect	Year	Person, Year	Year	Person, Year	Year	Person, Year	Year	Person, Year
Obs	9,803,852	9,219,773	9,803,852	9,219,773	8,738,058	8,157,266	8,738,058	8,157,266
Within R^2	0.613	0.411	0.259	0.074	0.543	0.396	0.242	0.075

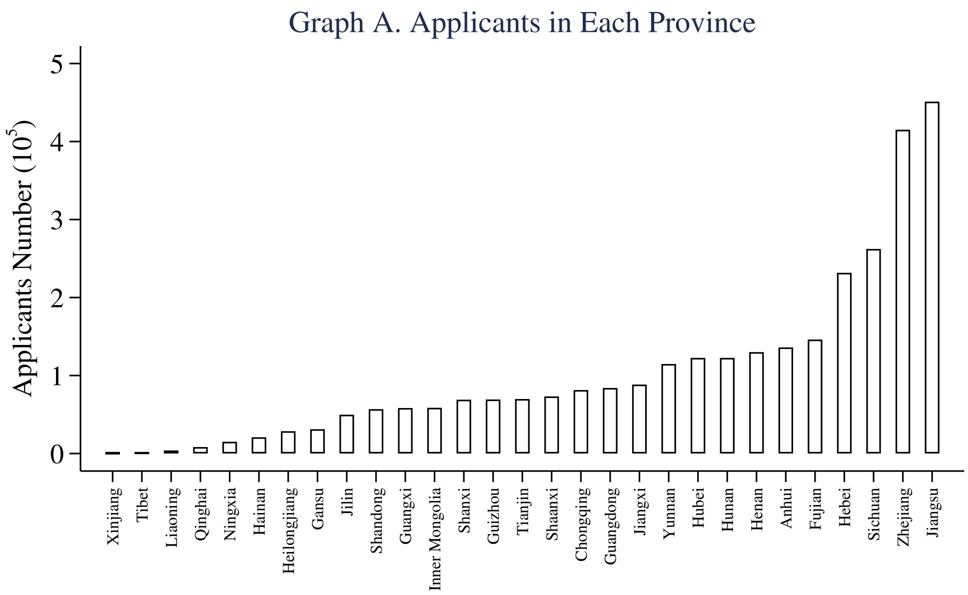
Table 10. Risk Aversion around Calendar Events

This table reports event studies of risk aversion around China's major calendar events. The sample is restricted to policies issued within one week before, during, and one week after each event. Event is an indicator for the event period and Post1w is an indicator for the one-week post-event period; the pre-event week serves as the benchmark. Columns 1–4 pool all four holidays: New Year's Day, Spring Festival, Workers' Day, and National Day. Columns 5–8 report results for New Year's Day only, which in China coincides with the fiscal year-end. Columns 9–12 report results for Spring Festival only, which coincides with the bonus season. All specifications control for person and year fixed effects. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. Reported in parentheses are t-statistics with standard errors two-way clustered by province and year in all specifications.

	1	2	3	4	5	6	7	8	9	10	11	12
	Four Holidays				Fiscal Year-End: New Year				Bonus Season: Spring Festival			
	ARA	Ln(ARA)	RRA	Ln(RRA)	ARA	Ln(ARA)	RRA	Ln(RRA)	ARA	Ln(ARA)	RRA	Ln(RRA)
Event	−0.090	0.066**	−0.283	0.060**	0.106	−0.022	−0.009	−0.032	−0.024	0.024	−0.068	0.030
	(−1.59)	(3.06)	(−1.91)	(2.80)	(0.50)	(−0.54)	(−0.02)	(−1.00)	(−0.14)	(0.47)	(−0.06)	(0.29)
Post1w	−0.005	0.034**	−0.048	0.035**	0.184	−0.030	0.254	−0.030	−0.059	0.024	−0.214	0.026
	(−0.13)	(2.55)	(−0.35)	(2.70)	(0.77)	(−0.62)	(0.39)	(−0.70)	(−0.53)	(0.78)	(−0.59)	(0.72)
Age	−0.031	0.054	−0.162	0.056	−0.697	−0.075	−2.649	−0.084	3.774**	0.016	12.751***	0.706
	(−0.11)	(0.98)	(−0.16)	(1.04)	(−1.52)	(−1.27)	(−1.69)	(−1.31)	(3.43)	(0.02)	(4.22)	(0.99)
LnExpense	4.941***	0.681***	13.835***	0.648***	5.190***	0.705***	14.295***	0.665***	5.569***	0.674***	15.920***	0.639***
	(7.39)	(5.71)	(7.50)	(5.21)	(7.01)	(5.01)	(7.42)	(4.45)	(6.50)	(4.30)	(6.97)	(3.87)
LnCoverage	−29.182***	−3.030***	−79.731***	−3.060***	−30.216***	−3.073***	−82.838***	−3.095***	−31.700***	−3.054***	−87.199***	−3.088***
	(−10.83)	(−19.35)	(−7.18)	(−21.27)	(−10.25)	(−32.58)	(−6.78)	(−39.39)	(−9.40)	(−28.39)	(−5.80)	(−35.47)
CarAge	−1.181***	−0.137***	−3.455***	−0.147***	−0.427*	−0.035	−0.930	−0.032	−1.033*	−0.141*	−3.446**	−0.165*
	(−4.34)	(−4.95)	(−4.14)	(−5.47)	(−2.06)	(−0.91)	(−1.22)	(−0.69)	(−2.41)	(−2.29)	(−2.80)	(−2.28)
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	890,167	890,167	764,014	764,014	227,211	227,211	195,018	195,018	115,369	115,369	97,843	97,843
Within R^2	0.345	0.078	0.323	0.080	0.356	0.079	0.340	0.081	0.348	0.071	0.323	0.073

Figure 1. Sample Distributions by Province

This figure shows the sample distribution across provinces. Graph A reports the number of applicants; Graph B reports the number of cars. There are 29 provinces in the sample. The final sample is a 5% random draw from the original China Insurance Information Technology Management (CIITC) sample.



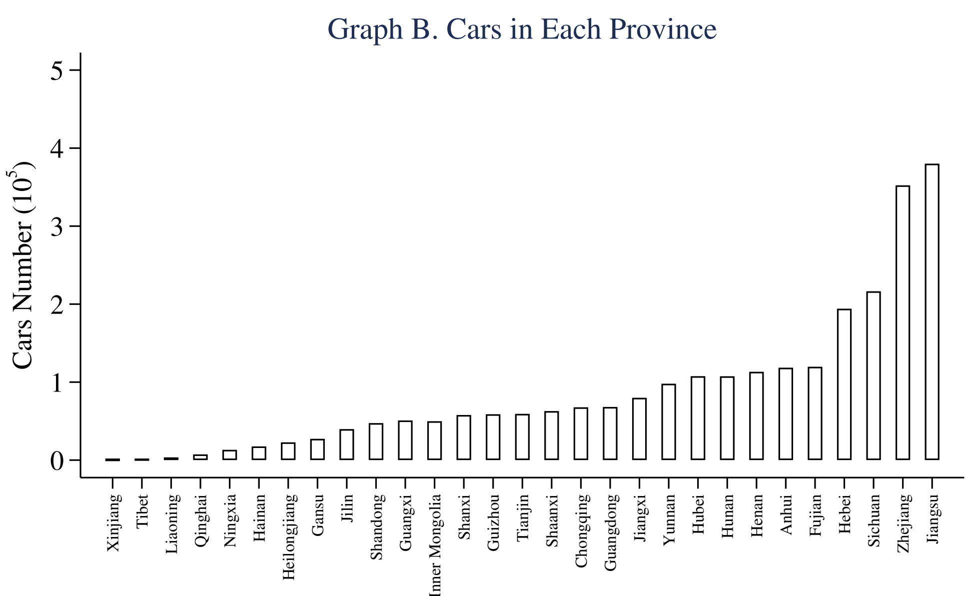


Figure 2. Average Risk Aversion and Quarterly Macro Indicators

This figure shows the average risk aversion with quarterly macro indicators. The dash-dotted line denotes absolute risk aversion (ARA), and the dashed line denotes relative risk aversion (RRA). The solid line denotes the quarterly growth rate of aggregate GDP in Graph A, the quarterly growth rate of aggregate retail sales in Graph B, the quarterly growth rate of aggregate industrial production in Graph C, and the quarterly growth rate of aggregate real estate investments in Graph D. The absolute risk aversion of each applicant in each quarter is measured using the method of Cohen and Einav (2007). Relative risk aversion is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. We average ARA and RRA across all applicants in each quarter. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

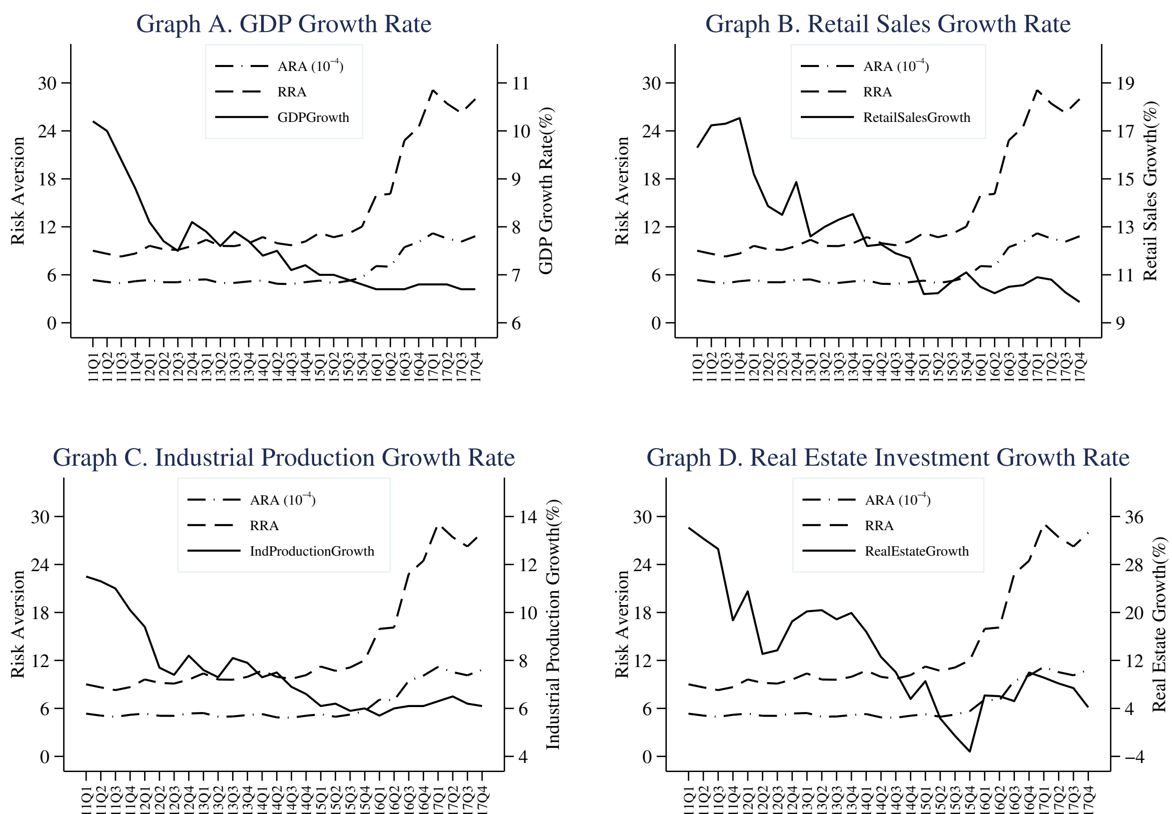
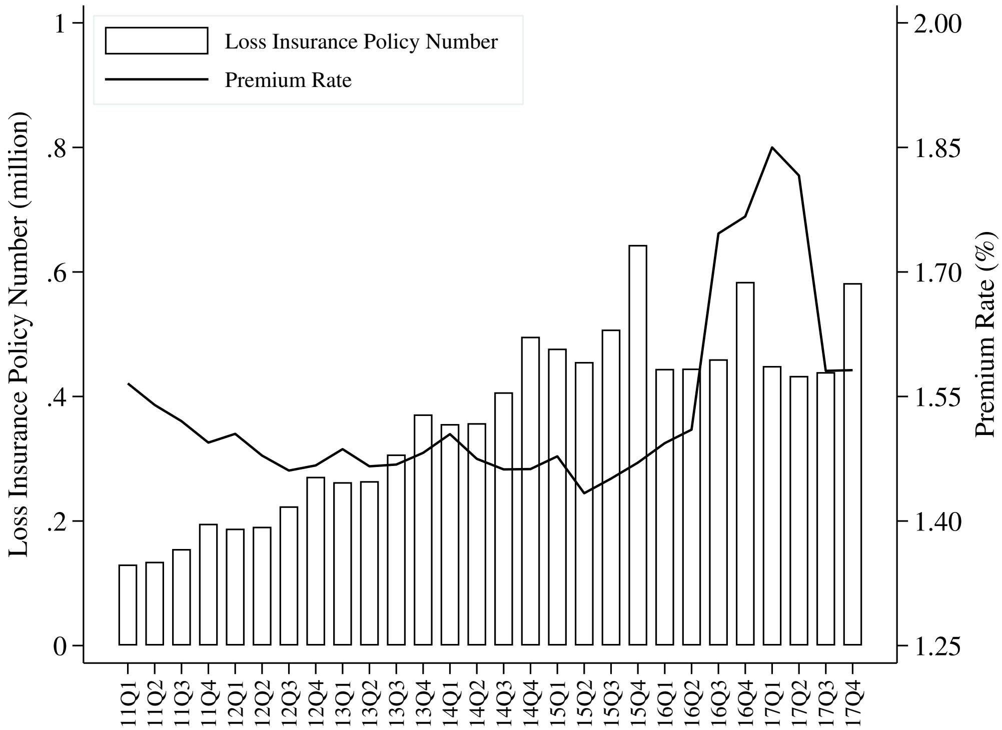


Figure 3. Number of Loss Insurance Policies and Average Premium Rate

This figure shows the number of loss insurance policies and the average premium rate in each quarter. The left axis shows the number of loss insurance policies in millions. The right axis shows the average premium rate, which is defined as the loss insurance premium divided by the loss coverage for each policy. The sample is from the first quarter of 2011 to the fourth quarter of 2017.



Supplementary Material for "Countercyclical Risk Aversion: Evidence from 10 Million Auto Insurance Transactions in China"

Section IA.1 describes the data. Section IA.2 derives conditions under which the panel regression of log relative risk aversion on the GDP growth rate is unbiased. Section IA.3 describes the supplementary tables, and Section IA.4 describes the supplementary figure. The supplementary tables and figure are collected at the end of this appendix.

IA.1. Description of the Data

The auto insurance platform of CIITC has collected nationwide insurance data and information for motor vehicles in China. The fully detailed data comprise 10 million policy-level records, which were randomly selected from the nearly 200 million policy-level records in the entire platform from 2011 to 2017, including first-time and repeat applications. For each record, the data contain the demographic characteristics of the applicant, the car attributes, the insurance clauses, and the claims within the duration of the policy. Below we list the variables available in the data for each record.

Demographics: Gender, Birth Date, Address, Postal Code.

Car Attributes: Vehicle Number (VIN), Last Check Date, Anti-skid Brake System (ABS Flag), Alarm Flag, Airbag Number, Risk Flag, Engine Number, First Registration Date, Years of Use, Model, Motor Type, New Vehicle Flag, Replacement Value, Whole Weight.

Insurance Clauses: Confirmation Sequence Number, Insurer, Coverage Code, Bill Date, Effective Date, Expire Date, Area Code, City Code, Loan Vehicle Flag, Renewal Flag, Sum Limit, Discount Value, Premium, Deductible, Deductible Discount.

Claims: Claim Sequence Number, Claim Type, Reporter, Loss Time, Accident Type, Accident Liability, Casualties (Medical Type), Recover Amount, Liability Rate, Loss Fee, Claim Amount, Accident Description.

IA.2. Log Relative Risk Aversion

In this appendix, we derive a result supporting the estimated coefficient in the panel regression (with fixed effects) of the log relative risk aversion on the GDP growth rate to be *unbiased* when relative risk aversion is estimated by the product of the individual's absolute risk aversion and the per capita consumption of the city in which the applicant lives.

Consider the panel regression model of individuals' relative risk aversion on the GDP growth rate:

$$Ln(RRA_{ijt}) = G_{ijt}\beta + \epsilon_{ijt} = G_{jt}\beta + \epsilon_{ijt}, \tag{IA.1}$$

where subscripts stand for individual i in city j at year t. The number of cities is K, and the number of years is T. There are N_j individuals in city j. The term G_{ijt} is the GDP growth rate of city j at year t, so it satisfies $G_{ijt} = G_{jt}$. The terms G and ϵ are assumed to be independent of each other and to have finite variance, which is similar to Petersen (2009). The intercept is suppressed for convenience.

The absolute risk aversion of individual i in city j at year t is ARA_{ijt}, and the annual consumption is C_{ijt}. We follow the standard risk aversion model to estimate the individual's relative risk aversion by multiplying absolute risk aversion by annual consumption: $RRA_{ijt} = ARA_{ijt} \times C_{ijt}$.

However, the annual consumption data of individuals are currently unavailable. We only have access to the individual's absolute risk aversion and the per capita annual consumption of city (C_{jt}) in which the applicant lives. So instead we estimate the relative risk aversion of individual i in city j at year t by multiplying absolute risk aversion by the per capita annual consumption of city j: $\widehat{RRA}_{ijt} = ARA_{ijt} \times C_{jt}$.

Since C_{jt} is the per capita annual consumption of city j at year t, it must satisfy the equation $C_{jt} = \sum_{i=1}^{N_j} \frac{C_{ijt}}{N_j}$. Define $C_{ijt} = C_{jt} \times (1 + \mu_{ijt})$; then clearly we have $\sum_{i=1}^{N_j} \mu_{ijt} = 0$.

Proposition 1. *When the individual's relative risk aversion is estimated by $\widehat{RRA}_{ijt} = ARA_{ijt} \times C_{jt}$, the estimated slope coefficient of the GDP growth rate from the model (IA.1) is unbiased if μ_{ijt} is independent and identically distributed, and after controlling for the individual fixed effects, the city fixed effects, or the year fixed effects.*

Proof. Since $RRA_{ijt} = ARA_{ijt} \times C_{ijt}$, we have the following equation:

$$Ln(\widehat{RRA}_{ijt}) = Ln(RRA_{ijt}) - Ln(\frac{C_{ijt}}{C_{jt}}). \tag{IA.2}$$

Using the ordinary least squares estimator and the formula (IA.2), the estimated slope coefficient of G from the model (IA.1) is given by

$$\begin{aligned}
\hat{\beta} &= \frac{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt} Ln(\widehat{RRA}_{ijt})}{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}^2} \\
&= \frac{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}(Ln(RRA_{ijt}) - Ln(\frac{C_{ijt}}{C_{jt}}))}{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}^2} \\
&= \beta + \frac{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}(\epsilon_{ijt} - Ln(1+\mu_{ijt}))}{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}^2}. \qquad \text{(IA.3)}
\end{aligned}$$

By Taylor's expansion, we have

$$Ln(1+\mu_{ijt}) = \mu_{ijt} - \frac{1}{2}\mu_{ijt}^2 + o(\mu_{ijt}^2). \qquad \text{(IA.4)}$$

Since μ_{ijt} is independent and identically distributed, we can define σ_C as the standard deviation of μ_{ijt}. Then we can derive from the law of large numbers that

$$\underset{N_j \to \infty}{plim} \left[\sum_{i=1}^{N_j} \frac{\mu_{ijt}^2}{N_j}\right] = \sigma_C^2. \qquad \text{(IA.5)}$$

Combining the equations in (IA.3) and (IA.4) and then (IA.5), we proceed to estimate the slope coefficient of G as

$$
\begin{aligned}
\hat{\beta} - \beta &= \frac{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}(\epsilon_{ijt} - \mu_{ijt} + \frac{1}{2}\mu_{ijt}^2 - o(\mu_{ijt}^2))}{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}^2} \\
&= \frac{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}\epsilon_{ijt}}{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}^2} - \frac{\sum_{t=1}^{T}\sum_{j=1}^{K} G_{jt}(\sum_{i=1}^{N_j}\mu_{ijt})}{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}^2} + \\
&\quad \frac{\sum_{t=1}^{T}\sum_{j=1}^{K} N_j G_{jt}(\sum_{i=1}^{N_j}(\frac{\mu_{ijt}^2}{2N_j} - o(\frac{\mu_{ijt}^2}{N_j})))}{\sum_{t=1}^{T}\sum_{j=1}^{K}\sum_{i=1}^{N_j} G_{jt}^2} \\
&= \underset{\substack{min\{N_j\} \to \infty \\ K,T\ fixed}}{plim} \left[\frac{1}{2}\frac{\sum_{t=1}^{T}\sum_{j=1}^{K} N_j G_{jt}}{\sum_{t=1}^{T}\sum_{j=1}^{K} N_j G_{jt}^2}\sigma_C^2\right]. \qquad \text{(IA.6)}
\end{aligned}
$$

The independence of G and ϵ is necessary for moving from the second equality to the third equality in (IA.6). The expression in (IA.6) shows that the estimated coefficient from (IA.1) is possibly biased.

However, if there are fixed effects in the model (IA.1), we can proceed as follows:

(1) If individual fixed effects are controlled for in the panel regression of model (IA.1), then the equivalent $\tilde{G}_{ijt} = G_{ijt} - \frac{1}{T}\sum_{x=1}^{T} G_{ijx} = G_{jt} - \frac{1}{T}\sum_{x=1}^{T} G_{jx}$, the equivalent $\tilde{\mu}_{ijt} = \mu_{ijt} - \frac{1}{T}\sum_{x=1}^{T}\mu_{ijx}$, and the equivalent $\tilde{\mu}_{ijt}^2 = \mu_{ijt}^2 - \frac{1}{T}\sum_{x=1}^{T}\mu_{ijx}^2$. We can infer that

$$
\sum_{i=1}^{N_j}\tilde{\mu}_{ijt} = \sum_{i=1}^{N_j}\mu_{ijt} - \frac{1}{T}\sum_{x=1}^{T}\sum_{i=1}^{N_j}\mu_{ijx} = 0, \qquad \text{(IA.7)}
$$

$$
\text{(IA.8)}\ \underset{N_j \to \infty}{plim}\left[\sum_{i=1}^{N_j}\frac{\tilde{\mu}_{ijt}^2}{N_j}\right] = \underset{N_j \to \infty}{plim}\left[\sum_{i=1}^{N_j}\frac{\mu_{ijt}^2}{N_j} - \frac{1}{T}\sum_{x=1}^{T}\sum_{i=1}^{N_j}\frac{\mu_{ijt}^2}{N_j}\right] = \sigma_C^2 - \frac{1}{T}\sum_{x=1}^{T}\sigma_C^2 = 0.
$$

Similar to (IA.6) and combining (IA.7) and (IA.8), we can obtain $\underset{\substack{min\{N_j\}\to\infty \\ K,T\ fixed}}{plim}\left[\hat{\beta}-\beta\right]=0.$

(2) If city (province) fixed effects are controlled for in the panel regression of model (IA.1), then the equivalent $\tilde{G}_{ijt}=G_{ijt}-\frac{1}{TN_j}\sum_{x=1}^{T}\sum_{z=1}^{N_j}G_{zjx}=G_{jt}-\frac{1}{T}\sum_{x=1}^{T}G_{jx}$, the equivalent $\tilde{\mu}_{ijt}=\mu_{ijt}-\frac{1}{TN_j}\sum_{x=1}^{T}\sum_{z=1}^{N_j}\mu_{zjx}=\mu_{ijt}$, and the equivalent $\tilde{\mu}_{ijt}^2=\mu_{ijt}^2-\frac{1}{TN_j}\sum_{x=1}^{T}\sum_{z=1}^{N_j}\mu_{zjx}^2$. According to (IA.5), we can infer that

(IA.9)
$$\sum_{i=1}^{N_j}\tilde{\mu}_{ijt}=\sum_{i=1}^{N_j}\mu_{ijt}=0,$$

(IA.10)
$$\underset{N_j\to\infty}{plim}\left[\sum_{i=1}^{N_j}\frac{\tilde{\mu}_{ijt}^2}{N_j}\right]=\underset{N_j\to\infty}{plim}\left[\sum_{i=1}^{N_j}\frac{\mu_{ijt}^2-\sigma_C^2}{N_j}\right]=0.$$

Similar to (IA.6) and combining (IA.9) and (IA.10), we can obtain $\underset{\substack{min\{N_j\}\to\infty \\ K,T\ fixed}}{plim}\left[\hat{\beta}-\beta\right]=0.$

(3) If time fixed effects are controlled for in the panel regression of model (IA.1), then the equivalent $\tilde{G}_{ijt}=G_{ijt}-\frac{\sum_{y=1}^{K}\sum_{z=1}^{N_y}G_{zyt}}{\sum_{y=1}^{K}N_y}=G_{jt}-\frac{\sum_{y=1}^{K}N_yG_{yt}}{\sum_{y=1}^{K}N_y}$, the equivalent $\tilde{\mu}_{ijt}=\mu_{ijt}-\frac{\sum_{y=1}^{K}\sum_{z=1}^{N_y}\mu_{zyt}}{\sum_{y=1}^{K}N_y}=\mu_{ijt}$, and the equivalent $\tilde{\mu}_{ijt}^2=\mu_{ijt}^2-\frac{\sum_{y=1}^{K}\sum_{z=1}^{N_y}\mu_{zyt}^2}{\sum_{y=1}^{K}N_y}$. According to (IA.5), we can infer that

(IA.11)
$$\sum_{i=1}^{N_j}\tilde{\mu}_{ijt}=\sum_{i=1}^{N_j}\mu_{ijt}=0,$$

$$\text{(IA.12)} \qquad \underset{min\{N_j\}\to\infty}{plim} \left[\sum_{i=1}^{N_j} \frac{\tilde{\mu}_{ijt}^2}{N_j}\right] = \underset{min\{N_j\}\to\infty}{plim} \left[\sum_{i=1}^{N_j} \frac{\mu_{ijt}^2 - \sigma_C^2}{N_j}\right] = 0.$$

Similar to (IA.6) and combining (IA.11) and (IA.12), we can obtain $\underset{\substack{min\{N_j\}\to\infty \\ K,T\ fixed}}{plim} \left[\hat{\beta} - \beta\right] = 0.$

Overall, the estimated slope coefficient of G in model (IA.1) with $\widehat{RRA}_{ijt} = ARA_{ijt} \times C_{jt}$ is *unbiased* under the assumption that the ratio of the individual's consumption to the per capita consumption of the city is independent and identically distributed, and after controlling for individual fixed effects, city (province) fixed effects, or time fixed effects.

□

IA.3. Supplementary Tables

This section describes how each supplementary table is constructed; the tables themselves are collected at the end of this appendix.

Table IA.I compares year-over-year claim statistics for two groups of policyholders: switchers who move from a 15% deductible in year T to a zero deductible in year $T + 1$ (Panel A), and non-switchers who hold a 15% deductible in both years (Panel B). For each group we report the average number of claims per policy, the average sum loss per policy, and the average minimum and maximum individual claim amounts per policy, in year T and in year $T + 1$, together with the difference ($T + 1$ minus T) and the corresponding paired t-statistics. The final rows report the difference-in-differences (Panel A minus Panel B), which nets out claim changes common to both groups, such as vehicle aging, learning, or mean reversion, together with t-statistics from two-sample t-tests.

Table IA.II reports difference-in-differences regressions of the premium rate that exploit the staggered rollout of the CIRC auto insurance pricing reform. The reform was introduced in three waves: six pilot jurisdictions on June 1, 2015 ($Treated_1$); twelve more on January 1, 2016 ($Treated_2$); and the remaining eighteen by July 1, 2016 ($Treated_3$). We estimate

$$\begin{aligned}\text{(IA.13)}\quad PremiumRate_{i,c,t} =& Treated_1 \times Post\_Jun2015_t + Treated_2 \times Post\_Jan2016_t \\ &+ Treated_3 \times Post\_Jul2016_t + Post\_Jun2015_t + Post\_Jan2016_t \\ &+ \alpha_i + \beta_c + \tau_t + X_{i,c,t} + \epsilon_{i,c,t},\end{aligned}$$

where α_i, β_c, and τ_t are person, jurisdiction, and year×quarter fixed effects; $Post\_Jun2015_t$, $Post\_Jan2016_t$, and $Post\_Jul2016_t$ are post-reform time indicators that equal one after each reform date; $Treated_1$, $Treated_2$, and $Treated_3$ indicate the three groups of jurisdictions; and X collects the controls Age, LnExpense, LnCoverage, and CarAge. Columns 1–2 report baseline regressions and Columns 3–4 add the three treatment-wave interactions; Columns 1 and 3 control for person and jurisdiction fixed effects, and Columns 2 and 4 add year×quarter fixed effects.

Table IA.III reports individual-level panel regressions of risk aversion on the lagged real quarterly GDP growth rate, with Panels A through D using lags of one through four quarters, respectively, and person fixed effects throughout.

Table IA.IV reports panel regressions of the four-quarter change in risk aversion (ΔARA and ΔRRA) on the real quarterly GDP growth rate. Panels A, B, and C control for person fixed effects, province fixed effects, and both person and year×quarter fixed effects, respectively.

Table IA.V reports individual-level panel regressions of risk aversion on alternative macro indicators, all under person fixed effects: the quarterly growth rate of industrial production (Panel A), retail sales (Panel B), and real estate investment (Panel C).

Table IA.VI reports individual-level panel regressions of risk aversion on the annual growth rate of per capita consumption within the province, under person fixed effects.

Table IA.VII reports panel regressions of risk aversion on the real annual GDP growth rate across all cities, estimated on a person-year panel because quarterly city-level GDP growth is unavailable for most cities. Panels A, B, and C control for person fixed effects, city fixed effects, and both person and year fixed effects, respectively.

Table IA.VIII reports panel regressions of risk aversion on the real quarterly GDP growth rate within the provincial capital cities, estimated on a person-quarter panel. Panels A, B, and C control for person fixed effects, city fixed effects, and both person and year×quarter fixed effects, respectively.

Table IA.IX reports province-quarter panel regressions in which risk aversion is averaged across individuals within each province and regressed on the quarterly growth rates of aggregate GDP, retail sales, industrial production, and real estate investment, controlling for province fixed effects.

Table IA.X reports panel regressions of risk aversion on the quarterly GDP growth rate within a quasi-balanced sample of individuals who buy at least one loss insurance policy every year. Panels A, B, and C control for person fixed effects, province fixed effects, and both person and year×quarter fixed effects, respectively.

Table IA.XI reestimates the baseline regressions of risk aversion on the real quarterly GDP growth rate (Panel A with person fixed effects, Panel B with province fixed effects) and reports t-statistics computed under several alternative standard-error clustering schemes.

IA.4. Supplementary Figure

Figure IA.I plots the distribution of the loss rate from a randomly selected sample of about 10,000 claims, together with the fitted lognormal probability density function used to compute $E(L)$ and $E(L^2)$ in the risk aversion formula.

Table IA.I. Within-Person Deductible Switchers vs. Non-Switchers

This table compares year-over-year claim statistics for switchers who move from a 15% deductible in year T to a zero deductible in year $T + 1$ (Panel A) and non-switchers who hold a 15% deductible in both years (Panel B). No. of Claims per Policy is the average number of claims filed per policy. Sum Loss per Policy is the average total claim amount per policy. Min Loss per Policy and Max Loss per Policy are the average minimum and maximum individual claim amounts per policy, respectively. Diff reports the difference between $T + 1$ and T, with t-statistics from paired t-tests. The final two rows report the difference between the two groups' year-over-year changes (Panel A minus Panel B), which absorbs vehicle aging, learning, and mean reversion common to both groups, together with t-statistics from two-sample t-tests.

	Obs	No. of Claims per Policy	Sum Loss per Policy	Min Loss per Policy	Max Loss per Policy
Panel A. Switchers (15% deductible in T, zero deductible in T+1)					
T	305,404	0.37	1027.45	715.26	921.20
T+1	305,404	0.17	503.14	343.82	448.29
Diff (T+1 minus T)		-0.20	-524.31	-371.44	-472.91
t-stat		-142.64	-53.58	-48.39	-51.65
Panel B. Non-switchers (15% deductible in both T and T+1)					
T	221,930	0.40	910.32	622.40	807.29
T+1	221,930	0.36	878.81	620.26	784.96
Diff (T+1 minus T)		-0.04	-31.51	-2.14	-22.33
t-stat		-24.61	-2.87	-0.25	-2.15
Diff-in-diff (A − B)		-0.15	-492.80	-369.29	-450.58
t-stat		-67.30	-33.52	-31.81	-32.56

Table IA.II. Auto Insurance Pricing Reform: Difference-in-Differences Analysis

This table reports difference-in-differences regressions of the premium rate exploiting the staggered rollout of the CIRC auto insurance pricing reform. The reform was first introduced in six pilot jurisdictions ($Treated_1$) on June 1, 2015, extended to an additional 12 jurisdictions ($Treated_2$) on January 1, 2016, and to the remaining 18 jurisdictions ($Treated_3$) by July 1, 2016. $Post\_Jun2015$, $Post\_Jan2016$, and $Post\_Jul2016$ are post-reform time indicators. The premium rate is defined as the loss insurance premium divided by the loss coverage, expressed as a percentage. Columns 1–2 report baseline regressions; Columns 3–4 include the DiD treatment interactions. Columns 1 and 3 control for person and jurisdiction fixed effects only; Columns 2 and 4 add year×quarter fixed effects. Demographic controls include Age, LnExpense, LnCoverage, and CarAge. Reported in parentheses are t-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
Dep. Var.: Premium Rate	Baseline		DiD with Reform Interactions	
$Treated_1 \times Post\_Jun2015$			−0.014	−0.009
			(−0.79)	(−0.57)
$Treated_2 \times Post\_Jan2016$			−0.006	−0.001
			(−0.66)	(−0.11)
$Treated_3 \times Post\_Jul2016$			−0.017	−0.011
			(−1.23)	(−0.90)
$Post\_Jun2015$			−0.004**	0.003
			(−2.05)	(1.45)
$Post\_Jan2016$			−0.006***	0.012***
			(−3.63)	(3.45)
Age	0.019***	−0.001	0.021***	−0.001
	(5.06)	(−1.08)	(5.38)	(−1.18)
LnExpense	1.574***	1.571***	1.573***	1.571***
	(50.28)	(47.45)	(49.79)	(47.55)
LnCoverage	−1.752***	−1.766***	−1.770***	−1.768***
	(−61.15)	(−59.18)	(−55.25)	(−56.48)
CarAge	−0.024***	−0.034***	−0.024***	−0.034***
	(−4.15)	(−4.77)	(−4.16)	(−4.77)
Person FE	Yes	Yes	Yes	Yes
Jurisdiction FE	Yes	Yes	Yes	Yes
Year×Quarter FE	No	Yes	No	Yes
Obs	9,649,944	9,649,944	9,649,944	9,649,944
Within R^2	0.924	0.918	0.924	0.919

Table IA.III. Regressions of Risk Aversion on Lagged GDP Growth Rate

This table reports the panel regressions of risk aversion on the lagged real quarterly GDP growth rate. Panels A through D report results for lags of one through four quarters, respectively. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real quarterly GDP growth rate of each province from the National Bureau of Statistics. We control for person fixed effects in all specifications. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Lag One Quarter				
lag_1(GDPGrowth)	-89.039***	-13.980***	-289.822***	-20.062***
	(-3.47)	(-2.89)	(-3.51)	(-3.55)
Fixed Effect	Person	Person	Person	Person
Obs	9,649,944	9,649,944	8,431,807	8,431,807
Within R^2	0.055	0.013	0.073	0.024
Panel B. Lag Two Quarters				
lag_2(GDPGrowth)	-87.374***	-13.793***	-280.167***	-19.401***
	(-3.58)	(-2.99)	(-3.66)	(-3.66)
Fixed Effect	Person	Person	Person	Person
Obs	9,649,944	9,649,944	8,431,807	8,431,807
Within R^2	0.059	0.014	0.076	0.025
Panel C. Lag Three Quarters				
lag_3(GDPGrowth)	-85.358***	-13.690***	-270.037***	-19.020***
	(-3.74)	(-3.15)	(-3.86)	(-3.86)
Fixed Effect	Person	Person	Person	Person
Obs	9,649,944	9,649,944	8,431,807	8,431,807
Within R^2	0.065	0.016	0.081	0.028
Panel D. Lag Four Quarters				
lag_4(GDPGrowth)	-82.754***	-13.596***	-259.327***	-18.648***
	(-3.82)	(-3.28)	(-4.09)	(-4.08)
Fixed Effect	Person	Person	Person	Person
Obs	9,649,944	9,649,944	8,431,807	8,431,807
Within R^2	0.074	0.019	0.090	0.032

Table IA.IV. Regressions of Changes in Risk Aversion on GDP Growth Rates

This table reports the panel regressions of changes in risk aversion on the real quarterly GDP growth rates. Panel A reports the panel regressions after controlling for person fixed effects. Panel B reports the panel regressions after controlling for province fixed effects. Panel C reports the panel regressions after controlling for both person and year×quarter fixed effects. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. ΔARA (ΔRRA) is the change in ARA (RRA) calculated by subtracting the ARA (RRA) four quarters prior from the current ARA (RRA). GDPGrowth is the real quarterly GDP growth rate of each province from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2
	ΔARA	ΔRRA
Panel A. Person Fixed Effect		
GDPGrowth	-64.686**	-184.841**
	(-2.58)	(-2.56)
Fixed Effect	Person	Person
Obs	5,870,930	5,122,391
Within R^2	0.018	0.021
Panel B. Province Fixed Effect		
GDPGrowth	-59.844***	-164.422***
	(-3.05)	(-2.93)
Fixed Effect	Prov	Prov
Obs	5,870,930	5,122,391
Within R^2	0.015	0.017
Panel C. Person and Year×Quarter Fixed Effects		
GDPGrowth	-16.760	-45.014
	(-0.77)	(-0.67)
Fixed Effect	Person, Year×Quarter	Person, Year×Quarter
Obs	5,328,174	4,594,786
Within R^2	0.001	0.001

Table IA.V. Regressions of Risk Aversion on Alternative Macro Indicators

This table reports the panel regressions of risk aversion on alternative macro indicators. Panel A, Panel B, and Panel C report the panel regressions of risk aversion on the quarterly growth rate of industrial production, retail sales, and real estate investments, respectively. We control for the person fixed effects in all specifications. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. IndGrowth is the quarterly growth rate of industrial production in each province. RetailGrowth is the quarterly growth rate of aggregate retail sales in each province. REstateGrowth is the quarterly growth rate of real estate investments in each province. The macro indicators are from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Regressions with Industrial Production Growth				
IndGrowth	-34.044**	-4.660*	-112.188**	-7.437**
	(-2.57)	(-1.75)	(-2.60)	(-2.32)
Fixed Effect	Person	Person	Person	Person
Obs	9,649,944	9,649,944	8,431,807	8,431,807
Within R^2	0.033	0.006	0.045	0.014
Panel B. Regressions with Retail Sales Growth				
RetailGrowth	-46.639**	-6.534*	-163.184***	-10.794**
	(-2.40)	(-1.76)	(-2.98)	(-2.68)
Fixed Effect	Person	Person	Person	Person
Obs	9,649,944	9,649,944	8,431,807	8,431,807
Within R^2	0.031	0.006	0.050	0.015
Panel C. Regressions with Real Estate Investments Growth				
REstateGrowth	-7.320**	-0.950	-25.851**	-1.690**
	(-2.28)	(-1.47)	(-2.65)	(-2.17)
Fixed Effect	Person	Person	Person	Person
Obs	9,646,009	9,646,009	8,428,550	8,428,550
Within R^2	0.021	0.003	0.031	0.009

Table IA.VI. Risk Aversion and Consumption

This table reports the panel regressions of risk aversion on consumption growth. We control for the person fixed effects in all specifications. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. ConsGrowth is the annual growth rate of per capita consumption in each province. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
ConsGrowth	-25.985**	-4.133**	-78.341**	-5.060**
	(-2.53)	(-2.19)	(-2.51)	(-2.24)
Fixed Effect	Person	Person	Person	Person
Obs	9,649,944	9,649,944	8,431,807	8,431,807
Within R^2	0.030	0.007	0.038	0.011

Table IA.VII. Regressions of Risk Aversion on Annual GDP Growth Rate in All Cities

This table reports the panel regressions of risk aversion on the real annual GDP growth rate in all cities. Panel A reports the panel regressions controlling for the person fixed effects. Panel B reports the panel regressions controlling for the city fixed effects. Panel C reports the panel regressions controlling for both person and year fixed effects. The absolute risk aversion (ARA) of each applicant at each year is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real annual GDP growth rate of each city from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by city and year in all specifications. The sample is from 2011 to 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Person Fixed Effect				
GDPGrowth	-71.835**	-12.007**	-239.116***	-17.137***
	(-2.44)	(-2.12)	(-2.87)	(-2.80)
Fixed Effect	Person	Person	Person	Person
Obs	9,646,770	9,646,770	8,730,298	8,730,298
Within R^2	0.048	0.013	0.066	0.024
Panel B. City Fixed Effect				
GDPGrowth	-58.973**	-13.471***	-209.481***	-18.957***
	(-2.56)	(-2.75)	(-3.13)	(-3.60)
Fixed Effect	City	City	City	City
Obs	9,646,770	9,646,770	8,730,298	8,730,298
Within R^2	0.013	0.011	0.026	0.019
Panel C. Person and Year Fixed Effects				
GDPGrowth	-2.302	1.239	8.233	1.983**
	(-0.45)	(1.16)	(0.66)	(2.10)
Fixed Effect	Person, Year	Person, Year	Person, Year	Person, Year
Obs	9,646,770	9,646,770	8,730,298	8,730,298
Within R^2	0.210	0.082	0.258	0.110

Table IA.VIII. Regressions of Risk Aversion on Quarterly GDP Growth Rate in Capital Cities

This table reports the panel regressions of risk aversion on the real quarterly GDP growth rate in capital cities. Panel A reports the panel regressions controlling for the person fixed effects. Panel B reports the panel regressions controlling for the city fixed effects. Panel C reports the panel regressions controlling for both person and year×quarter fixed effects. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real quarterly GDP growth rate of the capital city of each province from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors two-way clustered by city and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Person Fixed Effect				
GDPGrowth	-75.250***	-11.720***	-261.897***	-17.175***
	(-4.36)	(-3.54)	(-5.02)	(-4.98)
Fixed Effect	Person	Person	Person	Person
Obs	4,171,977	4,171,977	3,955,160	3,955,160
Within R^2	0.048	0.012	0.068	0.025
Panel B. City Fixed Effect				
GDPGrowth	-59.618***	-12.608***	-224.787***	-18.497***
	(-4.40)	(-4.09)	(-5.25)	(-5.65)
Fixed Effect	City	City	City	City
Obs	4,171,977	4,171,977	3,955,160	3,955,160
Within R^2	0.013	0.009	0.026	0.019
Panel C. Person and Year×Quarter Fixed Effects				
GDPGrowth	-11.749	0.513	-21.291	0.514
	(-1.17)	(0.20)	(-0.80)	(0.22)
Fixed Effect	Person, Year×Quarter	Person, Year×Quarter	Person, Year×Quarter	Person, Year×Quarter
Obs	4,171,977	4,171,977	3,955,160	3,955,160
Within R^2	0.001	0.000	0.000	0.000

Table IA.IX. Regressions of Risk Aversion on Macro Indicators at Province-Quarter Panel

This table reports the panel regressions of average risk aversion on the macro indicators in the province-quarter panel. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real quarterly GDP growth rate. IndGrowth is the quarterly growth rate of industrial production in each province. RetailGrowth is the quarterly growth rate of aggregate retail sales in each province. REstateGrowth is the quarterly growth rate of real estate investments in each province. Macro indicators are from the National Bureau of Statistics. We control for the province fixed effects in all specifications. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Risk Aversion on GDP Growth Rate				
GDPGrowth	-51.796***	-7.358***	-171.107***	-12.727***
	(-4.35)	(-4.56)	(-4.86)	(-6.14)
Fixed Effect	Prov	Prov	Prov	Prov
Obs	812	812	811	811
Within R^2	0.230	0.241	0.281	0.362
Panel B. Risk Aversion on Industrial Production Growth Rate				
IndGrowth	-23.512***	-3.373***	-78.742***	-5.981***
	(-4.14)	(-4.31)	(-4.69)	(-5.81)
Fixed Effect	Prov	Prov	Prov	Prov
Obs	812	812	811	811
Within R^2	0.202	0.216	0.253	0.341
Panel C. Risk Aversion on Retail Sales Growth Rate				
RetailGrowth	-38.347***	-5.579***	-127.853***	-9.734***
	(-4.19)	(-4.35)	(-4.82)	(-6.07)
Fixed Effect	Prov	Prov	Prov	Prov
Obs	812	812	811	811
Within R^2	0.230	0.253	0.286	0.387
Panel D. Risk Aversion on Real Estate Investment Growth Rate				
REstateGrowth	-4.322***	-0.608***	-14.258***	-1.091***
	(-3.30)	(-3.47)	(-3.70)	(-4.29)
Fixed Effect	Prov	Prov	Prov	Prov
Obs	808	808	807	807
Within R^2	0.098	0.100	0.119	0.163

Table IA.X. Quasi-Balanced Sample Analysis

This table reports the panel regressions of risk aversion on the quarterly GDP growth rate among the applicants who repeatedly apply for auto loss insurance. We keep only individuals who apply for at least one loss insurance policy every year. Panel A reports the panel regressions controlling for the person fixed effects. Panel B reports the panel regressions controlling for the province fixed effects. Panel C reports the panel regressions controlling for both person and year×quarter fixed effects. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real quarterly GDP growth rate from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. Reported in parentheses are *t*-statistics with standard errors two-way clustered by province and year×quarter in all specifications. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Person Fixed Effect				
GDPGrowth	-115.741***	-17.299***	-370.956***	-24.523***
	(-3.32)	(-2.86)	(-3.40)	(-3.50)
Fixed Effect	Person	Person	Person	Person
Obs	1,738,356	1,738,356	1,592,425	1,592,425
Within R^2	0.078	0.025	0.097	0.045
Panel B. Province Fixed Effect				
GDPGrowth	-115.097***	-17.242***	-369.130***	-24.599***
	(-3.54)	(-3.05)	(-3.70)	(-3.82)
Fixed Effect	Prov	Prov	Prov	Prov
Obs	1,738,356	1,738,356	1,595,737	1,595,737
Within R^2	0.040	0.014	0.060	0.026
Panel C. Person and Year×Quarter Fixed Effects				
GDPGrowth	-24.075*	2.197	-31.925	2.923
	(-1.79)	(0.53)	(-0.68)	(0.67)
Fixed Effect	Person, Year×Quarter	Person, Year×Quarter	Person, Year×Quarter	Person, Year×Quarter
Obs	1,738,356	1,738,356	1,592,425	1,592,425
Within R^2	0.002	0.000	0.000	0.000

Table IA.XI. Standard Errors Adjustment

This table reports the panel regressions of risk aversion on the real quarterly GDP growth rate. Panel A reports the panel regressions controlling for the person fixed effects. Panel B reports the panel regressions controlling for the province fixed effects. The absolute risk aversion (ARA) of each applicant is measured using the method of Cohen and Einav (2007). The relative risk aversion (RRA) is the product of absolute risk aversion and the annual per capita consumption of the city in which the applicant lives. GDPGrowth is the real quarterly GDP growth rate of each province from the National Bureau of Statistics. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors computed using various clustering approaches. The sample is from the first quarter of 2011 to the fourth quarter of 2017.

	1	2	3	4
	ARA	Ln(ARA)	RRA	Ln(RRA)
Panel A. Person Fixed Effect				
GDPGrowth	-86.739	-13.602	-293.244	-20.340
t-Stat clustered by Person	(-470.19)	(-248.59)	(-518.98)	(-337.15)
t-Stat clustered by Prov	(-5.53)	(-4.51)	(-4.95)	(-5.27)
t-Stat clustered by Quarter	(-4.55)	(-3.78)	(-5.41)	(-5.15)
t-Stat clustered by Prov*Quarter	(-10.22)	(-8.63)	(-10.59)	(-10.50)
t-Stat clustered by Person, Quarter	(-4.55)	(-3.78)	(-5.41)	(-5.15)
t-Stat clustered by Prov, Quarter	(-3.74)	(-3.08)	(-3.89)	(-3.93)
Fixed Effect	Person	Person	Person	Person
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.048	0.011	0.068	0.023
Panel B. Province Fixed Effect				
GDPGrowth	-68.413	-15.210	-242.217	-21.839
t-Stat clustered by Person	(-347.01)	(-271.27)	(-503.18)	(-360.05)
t-Stat clustered by Prov	(-5.77)	(-5.73)	(-5.36)	(-6.55)
t-Stat clustered by Quarter	(-4.51)	(-4.64)	(-5.54)	(-6.09)
t-Stat clustered by Prov*Quarter	(-10.34)	(-10.93)	(-11.38)	(-12.84)
t-Stat clustered by Person, Quarter	(-4.51)	(-4.64)	(-5.54)	(-6.09)
t-Stat clustered by Prov, Quarter	(-3.79)	(-3.82)	(-4.10)	(-4.76)
Fixed Effect	Prov	Prov	Prov	Prov
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.013	0.010	0.026	0.019

Figure IA.I. Distribution of Loss Rate

This figure shows the distribution of the loss rate from a randomly selected sample of about 10,000 claims. The vertical axis shows the frequency of each loss rate interval. The curve represents the fitted lognormal probability density function.