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

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Abstract

A fundamental idea in modern asset pricing is that risk aversion may be time varying and countercyclical (Campbell and Cochrane 1999). Existing evidence is scant and based mostly on experimental or survey data. We aim to test this key assumption using a large panel of real-world transaction data. Risk aversion is imputed from Chinese auto insurance policies, including 10 million transactions from 2011 to 2017. We find that individuals risk aversion is indeed time varying and countercyclical, after controlling for person and time fixed effects. The risk aversion measure behaves reasonably and also exhibits seasonal and "zodiac year" patterns. This paper illustrates how big data and alternative data can be employed to address key research questions in finance.

Keywords: Risk Aversion, Countercyclical, Auto Insurance

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1 Introduction

One leading explanation of various asset pricing puzzles is time-varying risk aversion (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 to explain a large number of important yet puzzling facts—for example, return predictability, high equity premium, and excess volatility, among many others. Such a feature also plays an important role in explaining the cross section of stock returns (see, e.g., Zhang (2005)).

While this feature is clearly of theoretical importance, direct empirical evidence on whether risk aversion indeed behaves this way is scant and based mostly on experimental or survey data. Cohn et al. (2015) study this question by priming financial professionals with either a boom or a bust scenario. Recently Guiso, Sapienza, and Zingales (2018) examine this question by using survey data on clients from one Italian bank.

Although evidence from experiments and survey data is helpful, such evidence is not a substitute for direct evidence from real transactions. In this paper, we examine this issue by estimating risk aversion from a large panel of individuals using data from real-world, non-stock-market transactions. In particular, utilizing China's comprehensive reporting of auto insurance policy data, we estimate risk aversion using auto insurance data following the seminal approach in Cohen and Einav (2007).[1]

We collect our data set from China Insurance Information Technology Management (CIITC), a government agency that aims to construct and operate a centralized and unified platform for sharing data and information on insurance in China. The data from the auto insurance platform of CIITC are comprehensive. We collect about 10 million auto insurance policies from 2011 to 2017, representing the entire population of 200 million auto insurance

[1]Cohen and Einav (2007) use one cross section of information on auto insurance deductible choices and thus do not examine the dynamic time-series properties of risk aversion.

policies in China.

In this paper, we find that the level of risk aversion imputed from the auto insurance data appears to be reasonable: it increases with individuals' age, is negatively related to lottery activity and stock trading activity in the region, and is positively related to regional insurance sales and bond trading activity.

More importantly, we find that risk aversion is indeed countercyclical. In our baseline individual-level specification with person fixed effects, a one-standard-deviation decrease in the GDP growth rate is associated with an increase of 5.3 in the relative risk aversion (RRA) coefficient (in the level regression), or a 36.6% increase in the RRA coefficient (in the log regression). To put these numbers into perspective, note that the mean and median RRA coefficients in our data sample are 15.112 and 7.818, respectively. These estimates suggest that the variation of risk aversion in the time series is economically large. These results provide direct and quantitative evidence for countercyclical variation in risk aversion, consistent with the consumption-based model with habit formation.

When we replace the macro indicator by the growth rate of aggregate retail sales, the growth rate of industrial production, or the growth rate of real estate investments, risk aversion is also negatively related to these macro indicators.

Furthermore, we explore the role of psychological forces in variations in individuals' levels of 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) by the number of nighttime hours during the fall and winter. The empirical evidence supports the idea that individuals' risk aversion indeed increases when the length of the night increases and that individuals are more risk averse in the fall and winter, consistent with the existing findings in the literature. 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. In China, a common belief is that people are at risk of experiencing misfortune in the zodiac year and should therefore be more cautious in case they experience bad luck (see also Fisman et al. 2019). Empirically, we find that an individual's imputed level of risk aversion indeed increases in the zodiac year, consistent with the hypothesis that psychological forces could affect the level of time-varying risk aversion.

The main finding in the paper is robust to different econometric specifications. We use several different methods of computing standard errors. We use GDP growth rates at both quarterly and annual frequencies. We use growth rates at the levels of provinces, capital cities, and all cities. Our main finding remains.

Recently, there has been a growing trend of using big data and alternative data to address key research questions in finance. Notable examples include Giglio, Liao, and Xiu (2021), as well as other studies highlighted in Goldstein, Spatt, and Ye (2021). Our paper contributes by employing insurance data, which are not commonly available, to investigate important asset pricing questions.

The rest of this paper is organized as follows. Section 2 describes the method of measuring risk aversion by the deductible choices from auto insurance data. Section 3 describes the data and the validity tests of risk aversion measures. Section 4 examines whether risk aversion is time varying and countercyclical. Section 5 provides additional explorations on the variation of risk aversion across seasons and in zodiac years. Section 6 provides robustness checks. Section 7 concludes.

2 Measuring Risk Aversion

2.1 Institutional Background

Although risk preference plays a vital role in decisions under uncertainty and economic analysis, measuring risk aversion has been quite 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 et al., 2012; Barseghyan et al., 2013). In this paper, we follow Cohen and Einav (2007) to estimate individuals' levels of risk aversion by exploiting the 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 the risk.

Our main data source is the auto insurance platform of China Insurance Information Technology Management (CIITC). CIITC aims to construct and operate a centralized and unified platform for sharing data and information in the main fields of insurance in China, which is public and comprehensive, serving the needs of the insurance industry. CIITC is able to pool and share 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, and the differentiation of individuals' deductible choices from the comprehensive auto insurance data make the screening model of risk preference in this paper plausible.

2.2 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 for 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 be generated by a Poisson process and known to individual i. In addition, there is no moral hazard in the model, so that λ_i is independent of the deductible choice. Therefore, by definition, a risk-neutral individual i would choose the low 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 an 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 the $u(w)$ 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

$$\begin{aligned} \lambda &= \lim_{t_i \to 0} \frac{\frac{1}{t_i}(u(w_i - I_i p_i^0 t_i) - u(w_i - I_i p_i^1 t_i))}{u(w_i - I_i p_i^1 t_i - I_i L d_i^1) - u(w_i - I_i p_i^0 t_i - I_i L d_i^0) - u(w_i - I_i p_i^1 t_i) + u(w_i - I_i p_i^0 t_i)} \\ &= \frac{(p_i^0 - p_i^1) I_i u^{'}(w_i)}{u(w_i - I_i L d_i^0) - u(w_i - I_i L d_i^1)}. \end{aligned} \tag{2}$$

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 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 mean and variance of the loss rate, respectively.

2.3 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 $p_i^1 = 0$. So we can rewrite the formula of absolute risk aversion in (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 instance, we randomly select about 10,000 claims, and the fitted loss rate is plotted in Figure 1. One can see that the loss rate of claims is approximately lognormally distributed, as is typically assumed in the literature. In our sample data set, the mean and variance of the loss rate are 0.02 and 0.00285, respectively.

In an econometric exercise, we try to use the observable data, which are 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 (6) and the variable r_i in (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 (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 (9) and the result in (10), we can estimate the parameters β and γ from the auto insurance data and then predict the variables λ_i and r_i. In practice, we use the Markov Chain Monte Carlo (MCMC) algorithm, specifically the 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.

3 Insurance Data and Risk Aversion

3.1 Insurance Data

The original sample from the auto insurance platform of CIITC comprises 10 million policy-level records, which are randomly selected from the nearly 200 million policy-level records in the entire platform, from 2011 to 2017, including all first-time and repeated applications. For

each record, the data contain demographic characteristics of the applicant, car attributes, insurance clauses, and claims within the duration of the policy. Appendix A.1 reports a description of the fully detailed sample.

In this sample, auto insurance applications are aggregated on a quarterly basis for each applicant.[2] 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 2. Jiangsu and Zhejiang have the most applicants, while Xinjiang and Tibet have the least. In addition, we also collect the province-level and city-level macro outputs and consumption data, lottery sales data, and stock performance data from the WIND database.

3.2 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—estimated by the approach described in Section 2—has an average of 6.842×10^{-4} CNY^{-1}. It is about 4 and 14 times higher than the similar estimates of 1.02×10^{-3} USD^{-1} in Cohen and Einav (2007) for auto insurance applicants and 3.1×10^{-4} USD^{-1} in Gertner (1993) for television game show participants. Since the exchange rate of US dollar to Chinese CNY is between 6 and 7 from 2011 to 2017, our estimates are largely consistent with the literature.

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

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

of estimated relative risk aversion. The missing observations are due to the unavailable consumption data in particular 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 to 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 2.912 years on average. The real quarterly growth rate of GDP of provinces in our sample has an average of 8.7% with a standard deviation of 1.8%. As alternative macroeconomic indicators, the mean of the real quarterly growth rate of industrial production, aggregate retail sales, and real estate investments at each province are 9.0%, 11.9%, and 12.4%, respectively. Additionally, individuals' consumption has an annual growth rate of 8.4% with a standard deviation of 3.6%.

3.3 Validity of Risk Aversion Estimates

Although risk aversion has long been discussed in theoretical studies, quantitatively measuring individuals' risk aversion is not easy. A strand of empirical studies measure risk preferences by hypothetical survey questions, such as Dohmen et al. (2011), Barsky et al. (1997), and Guiso, Sapienza, and Zingales (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 along several different angles.

First, we estimate panel regressions to test whether the estimated risk aversion is correlated to individuals' demographic characteristics. The results are reported in Table 2. We estimate panel regressions with no fixed effect or year dummies with the dependent variable to be the log of the absolute risk aversion measure, as reported in Columns 1 and 2, or the log of the relative risk aversion measure, as reported in Columns 3 and 4. In the Chinese auto insurance market, we do not find significant evidence supporting the inference that females are more risk averse than males. In fact, male applicants appear to be as risk averse as female applicants for their deductible choice, and the estimated coefficients of gender are statistically indistinguishable from zero. The estimated coefficients of age show an increasing pattern of individuals' risk aversion over the life cycle: individuals get more risk averse as they grow older. In sum, we find that applicants' risk aversion measure varies with age.

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 et al. (2008). In another paper, Guiso, Sapienza, and Zingales (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 at 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 insurance sales as the dependent variable in order to mitigate the influence of autocorrelations. The results are reported in Columns 1 and 2 of Table 3. Column 1 shows that the growth rate of lottery sales is negatively correlated to 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 -4.52. In Column 2, we reestimate the panel regression with $Ln(RRA)$ as the explanatory variable. The relative risk aversion indicator has an estimated coefficient of -0.140 with a t-statistic of -5.16, 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 means that individuals are less likely to buy lotteries as they get more risk averse, a finding consistent with the literature. The results are similar to the results when the independent variable is the raw value of absolute risk aversion or relative risk aversion.

In addition to lottery sales growth, we further 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 by 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. Similar to the analysis on 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, the estimated coefficient of $Ln(ARA)$ is 0.124, which is highly significant with a t-statistic of 3.99. Column 4 also shows that the log of relative risk aversion is positively correlated to the change in the log of aggregate insurance sales, with an estimated coefficient of 0.111 and a t-statistic of 4.78. 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 indicate that individuals with a higher value of risk aversion measures prefer to purchase more insurance policies.

Furthermore, we provide evidence for the validity of our measure of risk aversion by testing the correlation between risk aversion and how households allocate their wealth between risky and riskless assets. Our test leverages the idea that investors who have a lower level of risk aversion would invest more of their wealth in risky assets, which is the conventional wisdom in studies of household finance, such as 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 show that relative stock trading volume is negatively correlated to the log of absolute risk aversion with a coefficient of -0.196 and negatively correlated to 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 to the log of absolute risk aversion with a coefficient of 0.184 and positively correlated to the log of relative risk aversion with a coefficient of 0.129, and both are statistically significant, 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 show that individuals would invest less in stocks and more in bonds when they have a higher value of risk aversion measures.

Overall, we find that our measures of risk aversion are consistent with the existing estimates in literature. First, they are similar in magnitude. Second, our risk aversion measures are increasing with individuals' age. Furthermore, we find that individuals with a higher value of risk aversion measures are less likely to buy lotteries and stocks but more likely to buy insurance and bonds, meaning that individuals with a higher value of risk aversion measures are indeed more risk averse in their action choices with respect to other risky assets. These results are also consistent with the domain generality in risky assets preferences (Einav et al., 2012), which means that the relative ranking of individuals' risk preferences is stable across contexts.

4 Time-Varying and Countercyclical Risk Aversion

4.1 Aggregate-Level Indication

In a seminal paper, Campbell and Cochrane (1999) built a consumption-based model to jointly explain a number of important asset pricing phenomena with a time-varying and countercyclical risk premium or risk aversion as the core of the model. 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 empirical evidence of time-varying and countercyclical risk aversion. The closest result to this idea might be the study of Guiso, Sapienza, and Zingales (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 didn't 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.

Clearly, with continuous measures of individuals' risk aversion, we can first identify whether the risk aversion is fluctuating over time at the aggregate level.[3] 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 3, we plot the aggregate absolute risk aversion and relative risk aversion together with macroeconomic indicators, including aggregate GDP growth rate, aggregate retail sales growth rate, aggregate industrial production growth rate, and aggregate real estate investment growth rate. In Panel 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. Moreover, aggregate relative risk aversion slightly 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. Panel 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 Panel C, we see that the quarterly growth rate of aggregate industrial production also dropped from above

[3]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, Sapienza, and Zingales (2018). We focus on whether the individuals' risk aversion varies in time in this paper.

10% in 2011 to around 6% after 2015 with a minimum of 5.7% in the 1^{st} quarter of 2016 when both aggregate absolute risk aversion and aggregate relative risk aversion began to increase rapidly. Again, as shown in Panel 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 panels, we find that macroeconomic indicators vary earlier, and more importantly, counter to risk aversion. The lagged reaction of risk aversion might attribute to the general insensitiveness of individuals to macroeconomic variations. To quickly summarize, Figure 3 offers preliminary evidence that risk aversion appears to be time varying and countercyclical, as judged from the countervariations to macroeconomic indicators.

Different from the variation of the risk aversion measure at the cross section, the time-varying risk aversion measure in the paper might be influenced by the change in the auto insurance price at the aggregate level 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 4. 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 4^{th} quarter than in other quarters. Regarding the loss insurance price, the average premium rate fluctuated around 1.5% before the 2^{nd} quarter of 2016 and then increased to about 1.85% in the 1^{st} 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, we believe that aggregate-level time-varying and countercyclical risk aversion is not explained by the change in the auto insurance price.

4.2 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.

4.2.1 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 the fixed effect (individual fixed effect, city fixed effect, or time fixed effect) is controlled, the estimated slope coefficient of GDPGrowth proves to be *unbiased*. See Appendix A.2 for details.

Table 4 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 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 effect. Similar to Pastor, Stambaugh, and Taylor (2017), the ordinary least squares estimator controlling for the person fixed effect 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 rules out the potential effect of personal characteristics, such as demographics and wealth endowment, on risk aversion. In Column 1, the regression coefficient of GDPGrowth is -86.739, which is highly significant with a t-statistic of -3.74, meaning that the individual's absolute risk aversion is negatively correlated to 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 growth rate of GDP is associated with a 24.5% increase in the individual's absolute risk aversion. For the individual's relative risk aversion, Column 3 shows it to be negatively correlated to the GDP growth rate with an estimated coefficient of -293.244, remaining statistically significant at the 1% level. Column 4 reports the unbiased coefficient estimator of GDPGrowth with the natural logarithm of relative risk aversion as the dependent variable. The estimated coefficient is -20.340 and highly significant. The magnitude of the coefficient means that a one-standard-deviation decrease in the quarterly growth rate of GDP is associated with an increase in the relative risk aversion coefficient of 5.3 in the level regression, or a 36.6% increase in the individual's relative risk aversion in the log regression. 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.

Panel B reports the results of panel regressions controlling for the province fixed effect.

The regression coefficient essentially captures the average covariation of risk aversion and the GDP growth rate within the province. However, there is no cross-sectional variation of 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 the province fixed effect 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 highly significant (t-statistic=-4.76). Considering the economic significance, Columns 2 and 4 show that, within the province, a one-standard-deviation increase in the quarterly growth rate of GDP is associated with a 27.4% decline in the individual's absolute risk aversion and a 39.3% decline 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 effect, the addition of the time fixed effect would additionally control for the aggregate variation of variables over time but not the variation across individuals. To be easily understandable, the slope coefficient would

reflect 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 the change of aggregate economic trends.

4.2.2 Lag Reaction Effect

In previous aggregate-level analysis, the variation of individuals' risk aversion lags behind macroeconomic indicators. To further investigate the lag reaction effect of risk aversion to economic changes, we estimate individual-level panel regressions of risk aversion on the lagged GDP growth rate.

Table 5 reports the results of time-series regressions and reflects two noteworthy findings. First, the lag reaction effect of risk aversion variation to the GDP growth rate indeed exists at the time series, at least when the duration of the lag is shorter than one year. As shown in the columns of Table 5, the slope coefficients of lagged GDPGrowth remain economically and statistically significant for both absolute risk aversion and relative risk aversion when the lag duration ranges from one quarter to four quarters. Second, the lagged reaction of risk aversion to the GDP growth rate decays as the duration of the lag increases. When focusing on the relative risk aversion measure in Columns 3 and 4, we see that the slope coefficient of lagged GDPGrowth decreases monotonically in magnitude from -289.822 to -259.327 for raw relative risk aversion as the dependent variable and from -20.062 to -18.648 for the natural logarithm of relative risk aversion as the dependent variable, with the lag duration getting longer from one quarter to four quarters. We find a similar pattern in absolute risk aversion although the decay rate is lower than that of relative risk aversion.

4.2.3 Quasi-Balanced Sample Analysis

To further investigate the time-series covariation of individuals' risk aversion and the GDP growth rate, we estimate panel regressions among individuals who continue to buy auto insurance every year.[4] There are three reasons for the analysis in this quasi-balanced sample. First, for the aggregate-level analysis, the change in the distribution of insurance applicants might lead to fluctuations of aggregate risk aversion. As shown in Section 3, each applicant has about three or four applications for auto insurance on average in the sample, indicating the sample imbalance. The exit of old drivers and the entrance of new drivers may influence the average of risk aversion since they may possibly differ in their levels of risk aversion. Second, in the individual-level panel regressions, the slope coefficients do not reflect an *equal*-weighted average effect across individuals when the panel data are unbalanced. For instance, According to Pastor, Stambaugh, and Taylor (2017), the ordinary least squares estimator with person fixed effects places a larger weight on the time-series slopes of individuals with more observations in the sample. Thus, focusing on the individual-level panel regressions in a more balanced sample would allow us to find better quantitative estimators. Third, the analysis on individuals with a longer sample period would better capture the covariation between risk aversion and economic trends since there would be more cyclical variations for the GDP growth rate over a longer period of time.

Table 6 reports the results. In the quasi-balanced sample analysis, we find statistically significant and economically stronger evidence for the time-series negative correlation between the individual's risk aversion and the GDP growth rate. The estimated coefficient of GDPGrowth is -370.956 on the raw relative risk aversion and -24.523 on the natural logarithm of relative risk aversion; both are significant at the 1% statistical level and larger than

[4]In the person-quarter panel, ideally we should only keep individuals who continue to buy auto insurance each quarter in order to get a perfectly balanced panel. However, this condition would restrict our sample to a very small group of rich applicants, which would not be representative. Here, we keep individuals who continue to buy auto insurance every year in order to get a quasi-balanced panel instead.

those from the full sample regressions. The results for absolute risk aversion are similar. In addition, the estimated coefficients from panel regressions with the person fixed effect and the province fixed effect are very close in the quasi-balanced sample, meaning that the estimated coefficient of GDPGrowth controlling for the province fixed effect indeed captures the average time-series correlation between risk aversion and the GDP growth rate.

4.2.4 Alternative Macro Indicators

In this section, we use alternative macro indicators instead of the GDP growth rate to test the countercovariation of risk aversion and economic trends. We report the time-series regressions at the individual level in Table 7.

In Panel A, we find a negative correlation between risk aversion and the industrial production cycle. The estimated coefficient of IndGrowth is -7.437 for the natural logarithm of relative risk aversion, which is statistically significant with a t-statistic of -2.32, and -4.660 for the natural logarithm of absolute risk aversion, which is significant at the 10% statistical level. When we use the quarterly growth rate of retail sales as the independent variable and focus on the natural logarithm of relative risk aversion and absolute risk aversion in Panel B, the estimated coefficients of RetailGrowth (-10.794 and -6.534, respectively) are also statistically significant, meaning that the individual's risk aversion also varies countercyclically. In addition, we test the covariation between the individual's risk aversion and the growth of real estate investment in Panel C. The estimated coefficients of REstateGrowth are -1.690 with a t-statistic of -2.17 for the natural logarithm of relative risk aversion and -0.950 for the natural logarithm of absolute risk aversion, remaining negative although insignificant. In these panels, the statistical significance of macro indicators gets stronger when the dependent variable is the raw risk aversion measure rather than the natural logarithm.

More importantly, the magnitude of the above coefficient means that a one-standard-

deviation decrease in the quarterly growth rate of industrial production, aggregate retail sales, and real estate investments is associated, respectively, with a 26.8%, 25.9%, and 19.6% increase in the individual's relative risk aversion in the log regression. In sum, the results from alternative macro indicators show that the individual's risk aversion varies counter to economic trends, with considerable significance in quantity.

4.2.5 Changes in Consumption

In a seminal paper, Campbell and Cochrane (1999) built a model with the core of an i.i.d. consumption growth process, along with a slow-moving external habit in addition to the standard power utility function, and found that these features generate slow countercyclical variation in risk premia. The habit formation of consumption refers to the fact that consumers' reported sense of well-being is more sensitive to recent changes in consumption rather than to the absolute level of consumption. As consumption declines toward the habit level, the curvature of the utility function rises, and so do the expected risk premia.

In this section, we analyze the relation between the changes in individuals' consumption and their risk preferences. One noteworthy issue is that, in the model of Campbell and Cochrane (1999), the individual's habit formation is external and depends on the history of aggregate consumption rather than on the individual's own past consumption. In our analysis, we use the annual growth of per capita consumption within the province as the indicator of change in individuals' consumption, which reflects the change in consumption from an external habit level, consistent with the model.

Table 8 reports the panel regressions of risk aversion measures on consumption growth. In Columns 1 and 2, the estimated coefficient of the consumption growth rate is -25.346 (t-statistic=-2.50) for the raw absolute risk aversion parameter and -4.027 (t-statistic=-2.17) for the natural logarithm of the absolute risk aversion parameter, indicating a negative

and significant relation between the changes in consumption and absolute risk aversion. We then focus on the variation of relative risk aversion. As Columns 3 and 4 show, the estimated coefficient of the consumption growth rate is -76.477 for raw relative risk aversion and -4.936 for the natural logarithm of relative risk aversion, and both are statistically significant and economically stronger than those of absolute risk aversion. As a result, a one-standard-deviation decrease in the growth rate of consumption is associated with a 14.5% increase in the individual's absolute risk aversion and a 17.8% increase in relative risk aversion from the log regression. The results provide direct and quantitative evidence supporting countercyclical variation in risk aversion from the consumption-based model with habit formation.

Overall, we find a negative and robust correlation between the change of risk aversion and macroeconomic indicators in the time series. These results provide empirical evidence that risk aversion is time varying and countercyclical.

5 Additional Explorations

In theory, psychological forces could also shape individuals' risk preferences and thus lead to the change in risk aversion. Existing empirical studies find that the emotion of fear may be related to individuals' risk-taking behavior and play a critical role in countercyclical risk aversion (Lerner and Keltner, 2001; Cohn et al., 2015). In addition, seasonal mood swings, formally known as seasonal affective disorder (SAD) or "winter blues," can lead to seasonal variation in risk aversion, resulting in seasonal changes in returns and investing behaviors (Kamstra, Kramer, and Levi, 2003, 2015; Garrett, Kamstra, and Kramer, 2005; Kamstra et al., 2017). Another feature of psychology—superstition—could also have material consequences for individuals' risk-taking behavior (Fisman et al., 2023).

5.1 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, Kramer, and Levi, 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, Kramer, and Levi, 2003, 2015; Garrett, Kamstra, and Kramer, 2005; Kamstra et al., 2017). Kamstra et al. (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 conduct a direct test on seasonality in risk aversion with our measures. We follow Kamstra, Kramer, and Levi (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. SAD_t 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 9. City and year fixed effects are included in all specifications to control for the variations of risk aversion across cities and years.

In Panel A, Column 1 shows that absolute risk aversion appears to be positively correlated to 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 highly 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 show that individuals' risk aversion indeed increases with the length of the night and is higher in the fall and winter.

5.2 Zodiac Years

We follow Fisman et al. (2023) to investigate the role of superstition, specifically the "zodiac year effect," in the variation of 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 10, we estimate panel regressions of risk aversion measures on the zodiac year indicator. In the full sample 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 levels are statistically significant after controlling for demographic variables and car attributes. When we restrict the sample to the years around individuals' zodiac year, such as the seven-year or three-year window, the zodiac year effect gets stronger since the estimated coefficient of the zodiac year indicator is economically and statistically more significant. The results provide support for the hypothesis that psychological forces could lead to time-varying risk aversion; in this case, the individual's level of risk aversion would increase at the zodiac year every 12 years because of the individual's superstition.

6 Robustness Checks

6.1 Standard Errors Adjustment

In this paper, we mainly use the panel regression approach for empirical investigations. However, one challenge for panel data analysis is that the residuals in the data sets may be correlated across individuals or across time (Petersen, 2009). In the person-quarter panel regressions in this paper, we report t-statistics adjusted with standard errors clustered by both province and quarter. The adjustment procedure accounts for correlations across individuals, autocorrelations, as well as other correlations within the province.

To confirm the effectiveness of our adjustment procedure for standard errors in panel regressions, we reestimate the main regressions in the full sample, as shown in Table 4, and report t-statistics adjusted in various procedures in Table 11. Panel A shows that, for the panel regressions with person fixed effect, which capture the covariations between risk aversion and the GDP growth rate in the time series, we find that the standard error clustered by province or by quarter is much larger than that clustered by person, verifying the high correlation across individuals. Beyond that, the approach of clustering by both province and quarter generates the largest standard errors and accounts for the most correlations of residuals. The panel regressions with province fixed effect in Panel B show similar results. The overall results verify the validity of the statistical significance of the ordinary least squares estimators from the panel regressions in this paper.

6.2 City-Level Macro Indicators

In Section 4.2.1, we study the covariation between risk aversion and the quarterly growth rate of GDP in each province. In this section, we proceed to study the covariation more

precisely with city-level macro indicators.[5]

First, we redo the panel regressions of risk aversion measures on the city-level GDP growth rate in all cities. Since the quarterly growth rate of GDP is unavailable for most cities, we estimate regressions with person-year panel data. The results are reported in Table 12. Similar to the results of the baseline findings, the estimated coefficients of GDPGrowth in panel regressions with the person fixed effect or city fixed effect are significantly negative. When considering the variations at the time series, a 1% decrease in the annual GDP growth rate would be associated with a 12% increase in absolute risk aversion and a 17% increase in relative risk aversion. The economic significance gets slightly stronger for the estimated coefficients from panel regressions with the province fixed effect.

After that, we redo the panel regressions of risk aversion measures on the city-level GDP growth rate in the capital cities of all provinces. For capital cities, we estimate regressions with person-quarter panel data and report the results in Table 13. Compared with the baseline findings in all provinces, the results in the capital cities also show a negative relation between the change in risk aversion and the quarterly GDP growth rate, although the estimated coefficients are relatively smaller in magnitude (-11.720 for the natural logarithm of absolute risk aversion and -17.175 for the natural logarithm of relative risk aversion, smaller in magnitude than those from regressions in all provinces).

6.3 Aggregate-Level Regressions

In Section 4, we investigate the time-varying and countercyclical risk aversion by aggregate-level indication and individual-level regressions. We next test the results by aggregate-level regressions at the province-quarter panel for robustness. We calculate the average of risk aversion measures across individuals within the province as the aggregate risk aversion

[5]Relative to the 29 provinces, there are 295 cities in the sample and nearly 10,000 applicants, on average, in each city.

measure of the province. Using aggregate-level regressions has two advantages. On the one hand, the influence of correlation across individuals would vanish at the aggregate-level analysis. On the other hand, it could help attenuate the imprecision on individual-level regressions, especially when the sample period is not long.

As Table 14 shows, the negative and significant relation between risk aversion and macroeconomic indicators also exists at the aggregate-level analysis. We find negative estimated coefficients of the quarterly growth rate of aggregate GDP, the quarterly growth rate of aggregate retail sales, the quarterly growth rate of aggregate industrial production, and the quarterly growth rate of aggregate real estate investments, and all are significant at the 1% statistical level. Although the economic significance of macro indicators in aggregate-level regressions is less than that in individual-level regressions, the results verify the robustness of finding that risk aversion is time varying and countercyclical.

7 Conclusions

An important question in the asset pricing literature is whether individuals' risk aversion is time varying and countercyclical—a question that has not yet received a clear and decisive answer empirically. In this paper, we estimate individuals' risk aversion by the data on deductible choices in auto insurance contracts, which are designed to help individuals hedge against risk. Detailed and nationwide auto insurance data make the investigation into the time-series variation of risk aversion possible and fruitful. We find that our risk aversion estimates are on 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. Critically, we provide clear empirical evidence that risk aversion is time varying and countercyclical at both the aggregate level (indicatively) and the individual level (decisively). A one-standard-deviation decrease in the annual growth

rate of GDP is associated with a 36.6% increase in relative risk aversion.

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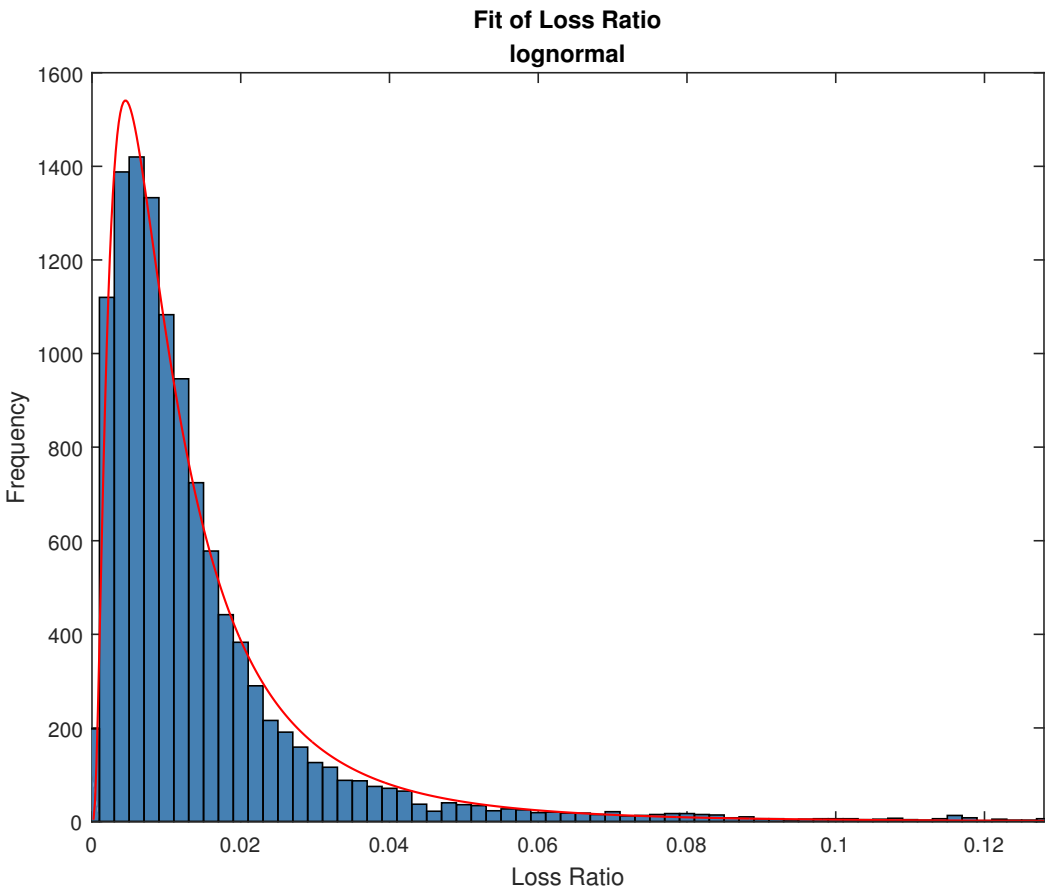


Figure 1: This figure shows the distribution of the loss rate from a randomly selected sample of about 10,000 claims. The vertical variable is the frequency of the loss rate interval. The curve represents the fitted lognormal probability density function.

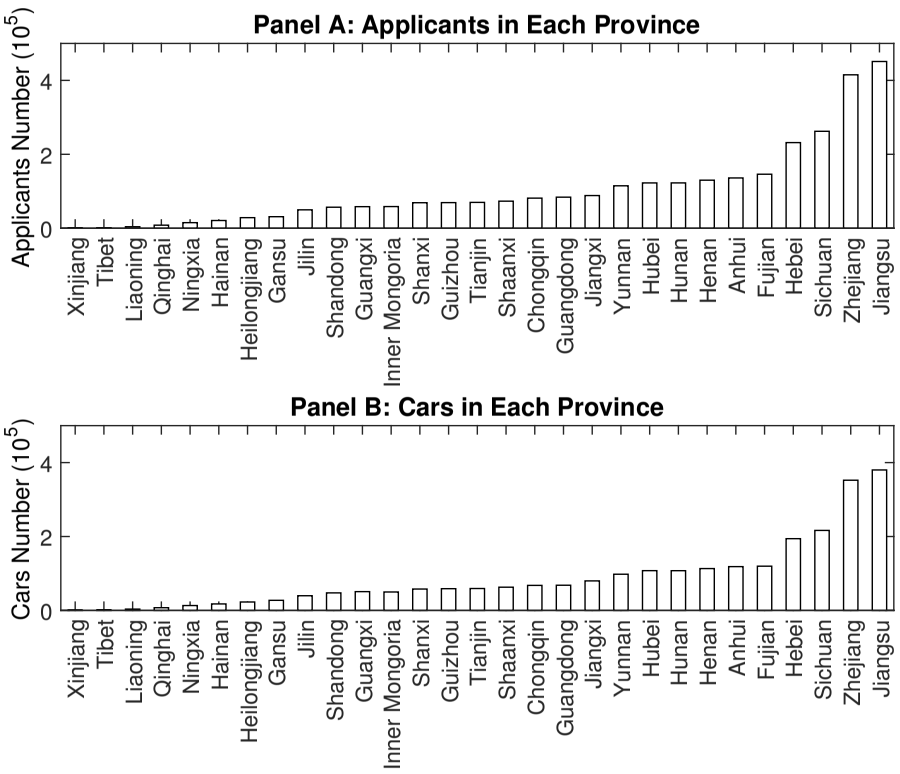


Figure 2: This figure shows the sample distributions in each province. The vertical variable in Panel A is the number of applicants. The vertical variable in Panel B is the number of cars. There are 29 provinces in the sample. The final sample is randomly selected from the original sample from CIITC with a share of 5%.

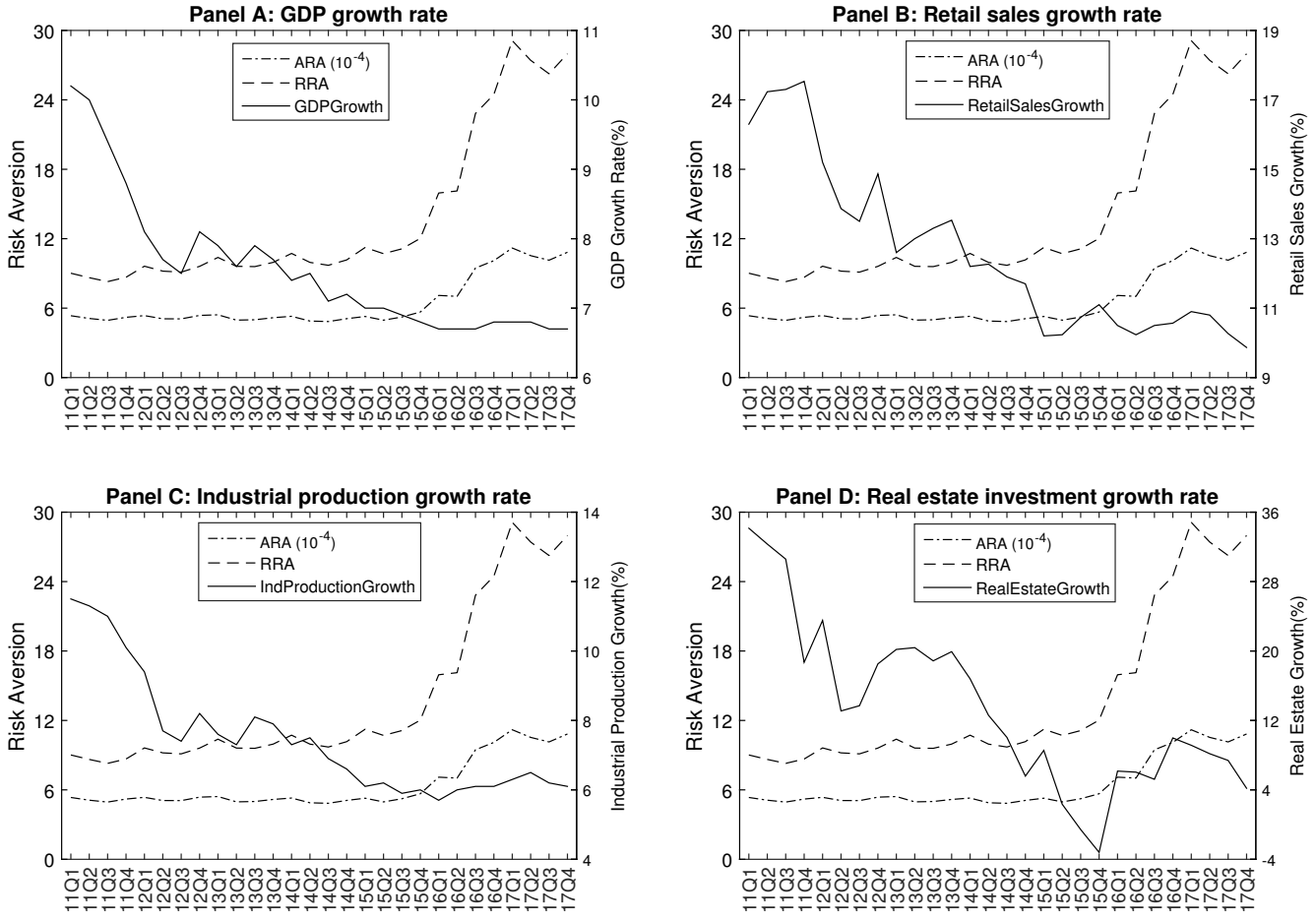


Figure 3: This figure shows the average risk aversion with quarterly macro indicators. The dashed and dotted line denotes absolute risk aversion (ARA), and the dashed line denotes relative risk aversion (RRA). The solid line denotes the quarterly growth rate of aggregate GDP in Panel A, the quarterly growth rate of aggregate retail sales in Panel B, the quarterly growth rate of aggregate industrial production in Panel C, and the quarterly growth rate of aggregate real estate investments in Panel D. The absolute risk aversion of each applicant at 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 the sample at each quarter. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

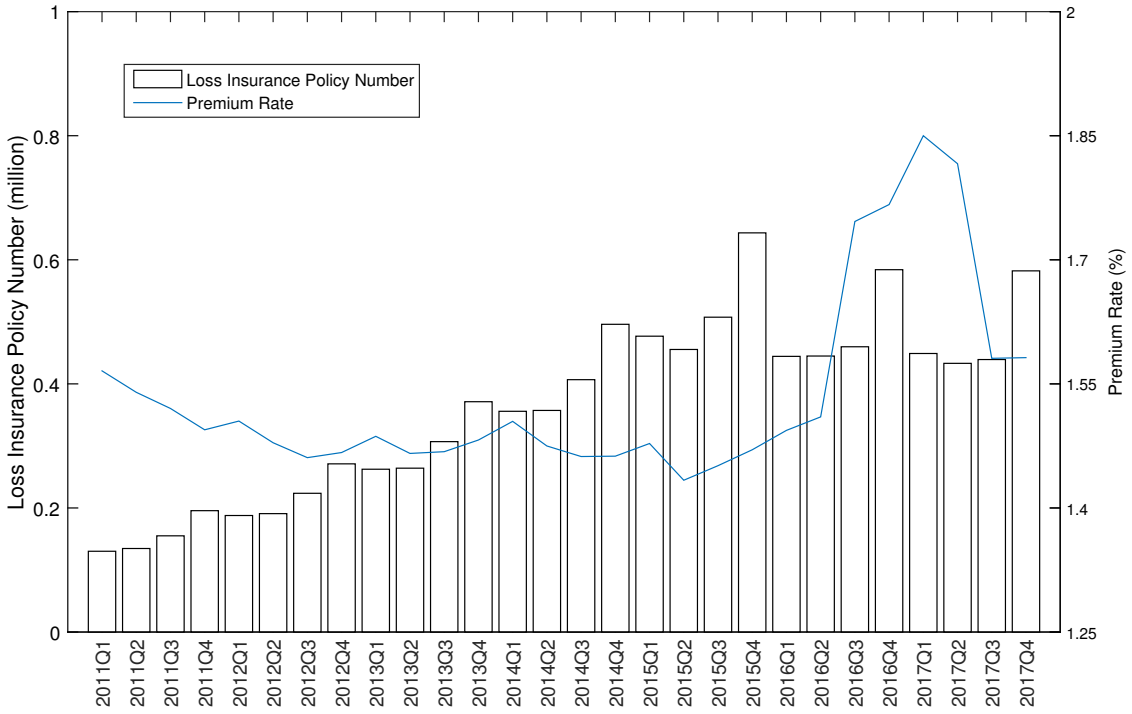


Figure 4: This figure shows the number of loss insurance policies and the average premium rate at each quarter. The variable in the left vertical is the number of loss insurance policies in millions. The variable in the right vertical is the average premium rate, which is defined as the loss insurance premium divided by the loss coverage for each policy. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

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. Gender 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 1^{st} quarter of 2011 to the 4^{th} 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
Gender	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 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. Gender 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 adjusted by two-way clustering in the dimensions of province and year×quarter in all specifications. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

	Ln(ARA)		Ln(RRA)	
	1	2	3	4
Gender	0.006	0.013	-0.010	0.002
	(0.60)	(1.59)	(-0.74)	(0.17)
Age	0.014***	0.014***	0.011***	0.012***
	(16.51)	(17.20)	(11.00)	(12.37)
LnExpense	0.634***	0.642***	0.523***	0.520***
	(6.75)	(11.03)	(5.53)	(8.68)
LnCoverage	-2.578***	-2.479***	-2.484***	-2.349***
	(-30.72)	(-42.62)	(-30.79)	(-42.56)
CarAge	-0.098***	-0.138***	-0.064***	-0.118***
	(-9.18)	(-12.33)	(-5.38)	(-10.09)
Constant	16.444***	15.332***	26.169***	24.740***
	(34.98)	(50.42)	(51.04)	(82.40)
Fixed Effect	No	Year×Quarter	No	Year×Quarter
Obs	10,229,255	10,229,255	8,997,276	8,997,276
Within R^2	0.283	0.259	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. The lottery sale is the sum of welfare lottery sale and sports lottery sale. 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 or their logs in the province. 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 the province fixed effect in all specifications. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors adjusted by two-way clustering in the dimensions of province and year×quarter in Columns 1 to 4, and in the dimensions of province and year in Columns 5 to 8. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017 for the province-quarter panel and from 2011 to 2017 for the province-year panel.

	ΔLn(Lottery)		ΔLn(Insurance)		RelStock		RelBond	
	1	2	3	4	5	6	7	8
Ln(ARA)	-0.169***		0.124***		-0.196**		0.184**	
	(-4.52)		(3.99)		(-2.49)		(2.25)	
Ln(RRA)		-0.140***		0.111***		-0.142**		0.129**
		(-5.16)		(4.78)		(-2.26)		(2.03)
Fixed Effect	Prov	Prov	Prov	Prov	Prov	Prov	Prov	Prov
Obs	812	811	812	811	202	202	202	202
Within R^2	0.126	0.173	0.159	0.253	0.205	0.217	0.176	0.179

	ΔLn(Lottery)		ΔLn(Insurance)		RelStock		RelBond	
	1	2	3	4	5	6	7	8
ARA	-0.023***		0.017***		-0.028***		0.026**	
	(-4.44)		(3.91)		(-2.61)		(2.32)	
RRA		-0.009***		0.007***		-0.009***		0.009**
		(-4.72)		(4.25)		(-2.61)		(2.39)
Fixed Effect	Prov	Prov	Prov	Prov	Prov	Prov	Prov	Prov
Obs	812	811	812	811	202	202	202	202
Within R^2	0.122	0.148	0.153	0.209	0.217	0.225	0.183	0.195

Table 4: 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 effect. Panel B reports the panel regressions controlling for the province fixed effect. 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 adjusted by two-way clustering in the dimensions of province and year×quarter in all specifications. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

Panel A: Person Fixed Effect

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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: Prov Fixed Effect

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
GDPGrowth	-15.154	0.876	-25.950	1.507
	(-1.52)	(0.25)	(-0.64)	(0.39)
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 5: 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. 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 effect in all specifications. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors adjusted by two-way clustering in the dimensions of province and year×quarter in all specifications. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
Panel A: lag 1 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 2 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 3 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 4 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 6: 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 only keep the accounts that apply for at least one loss insurance policy every year. Panel A reports the panel regressions controlling for the person fixed effect. Panel B reports the panel regressions controlling for the province fixed effect. 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 adjusted by two-way clustering in the dimensions of province and year×quarter in all specifications. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

Panel A: Person Fixed Effect

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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	0.056	0.026

Panel C: Person and Year×Quarter Fixed Effect

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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 7: 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 effect 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 adjusted by two-way clustering in the dimensions of province and year×quarter in all specifications. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

Panel A: Regressions with Industrial Production Growth

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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 8: Risk Aversion and Consumption

This table reports the panel regressions of risk aversion on consumption growth. We control for the person fixed effect 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 adjusted by two-way clustering in the dimensions of province and year×quarter in all specifications. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
ConsGrowth	-25.346**	-4.027**	-76.477**	-4.936**
	(-2.50)	(-2.17)	(-2.47)	(-2.21)
Fixed Effect	Person	Person	Person	Person
Obs	9,649,944	9,649,944	8,431,807	8,431,807
Within R^2	0.029	0.007	0.037	0.012

Table 9: 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, Kramer, and Levi (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 adjusted by two-way clustering in the dimensions of city and year in all specifications. The sample is from 2011 to 2017.

Panel A: Absolute risk aversion

	ARA			Ln(ARA)		
	1	2	3	4	5	6
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)		
	1	2	3	4	5	6
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 10: Zodiac Year Effect

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 equalling one for ages that are a multiple of 12 and zero otherwise. Gender 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. Columns 3 and 4 limit the sample to the ages within the seven-year window surrounding the zodiac year. Columns 5 and 6 limit the sample to the ages within the three-year window surrounding the zodiac year. We control for year dummies in all specifications All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors adjusted by two-way clustering in the dimensions of province and year in all specifications. The sample is from 2011 to 2017.

	Full Sample		years in [-3, 3]		years in [-1, 1]	
	Ln(ARA)	Ln(RRA)	Ln(ARA)	Ln(RRA)	Ln(ARA)	Ln(RRA)
	1	2	3	4	5	6
Zodiac	0.015***	0.016**	0.056***	0.057***	0.028***	0.030***
	(4.40)	(3.68)	(24.18)	(20.12)	(13.57)	(11.18)
Gender	0.013	0.002	0.011	-0.001	0.011	-0.003
	(1.41)	(0.15)	(1.43)	(-0.14)	(1.51)	(-0.28)
Age	0.014***	0.012***	0.018***	0.016***	0.017***	0.015***
	(16.25)	(12.51)	(15.79)	(13.88)	(13.96)	(11.83)
LnExpense	0.654***	0.539***	0.647***	0.533***	0.651***	0.539***
	(9.57)	(7.88)	(9.95)	(8.04)	(10.07)	(8.15)
LnCoverage	-2.498***	-2.374***	-2.490***	-2.365***	-2.497***	-2.373***
	(-35.27)	(-34.66)	(-36.57)	(-35.81)	(-35.79)	(-34.89)
CarAge	-0.138***	-0.118***	-0.137***	-0.117***	-0.138***	-0.118***
	(-9.50)	(-7.25)	(-9.17)	(-6.99)	(-9.30)	(-7.13)
Fixed Effect	Year	Year	Year	Year	Year	Year
Obs	9,803,852	8,738,058	3,415,761	3,047,027	1,631,764	1,455,228
Within R^2	0.259	0.242	0.256	0.239	0.257	0.240

Table 11: 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 effect. Panel B reports the panel regressions controlling for the province fixed effect. 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 adjusted in different approaches. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

Panel A: Person Fixed Effect

Dep.Var.	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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

Dep.Var.	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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

Table 12: 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 effect. Panel B reports the panel regressions controlling for the city fixed effect. 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 adjusted by two-way clustering in the dimensions of city and year in all specifications. The sample is from 2011 to 2017.

Panel A: Person Fixed Effect

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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	0.031	0.030	0.047	0.032

Panel C: Person and Year Fixed Effect

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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	0.000	0.000	0.000	0.000

Table 13: 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 effect. Panel B reports the panel regressions controlling for the city fixed effect. 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 adjusted by two-way clustering in the dimensions of city and year×quarter in all specifications. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

Panel A: Person Fixed Effect

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
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 Effect

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
GDPGrowth	-11.749	0.513	-21.291	0.514
	(-1.21)	(0.21)	(-0.83)	(0.23)
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	0.000	0.000	0.000	0.000

Table 14: 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 at 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 effect in all specifications. All variables are winsorized at the 1% and 99% level. Reported in parentheses are t-statistics with standard errors adjusted by two-way clustering in the dimensions of province and year×quarter in all specifications. The sample is from the 1^{st} quarter of 2011 to the 4^{th} quarter of 2017.

Panel A: Risk Aversion on GDP Growth Rate

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
GDPGrowth	-51.796***	-7.358***	-171.107***	-12.727***
	(-4.27)	(-4.48)	(-4.77)	(-6.02)
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
IndGrowth	-23.512***	-3.373***	-78.742***	-5.981***
	(-4.07)	(-4.23)	(-4.61)	(-5.70)
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
RetailGrowth	-38.347***	-5.579***	-127.853***	-9.734***
	(-4.12)	(-4.27)	(-4.73)	(-5.96)
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

	ARA	Ln(ARA)	RRA	Ln(RRA)
	1	2	3	4
REstateGrowth	-4.322***	-0.608***	-14.258***	-1.091***
	(-3.23)	(-3.40)	(-3.63)	(-4.20)
Fixed Effect	Prov	Prov	Prov	Prov
Obs	808	808	807	807
Within R^2	0.098	0.100	0.119	0.163

A Appendix

A.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 are 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 in the renewed data for each record.

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

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.

A.2 Log Relative Risk Aversion

In this appendix, we derive a result supporting the estimated coefficient in the panel regression (with fixed effect) 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:

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

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. G_{ijt} is the GDP growth rate of city j at year t, so it satisfies $G_{ijt} = G_{jt}$. 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 $C_{jt} = \sum_{i=1}^{N_j} \frac{C_{ijt}}{N_j}$. Let's 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 (A.1) is unbiased if μ_{ijt} is independent and identically distributed, and after controlling for the individual fixed effect, the city fixed effect, or the year fixed effect.

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

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

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

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

By Taylor's expansion, we have

$$Ln(1+\mu_{ijt}) = \mu_{ijt} - \frac{1}{2}\mu_{ijt}^2 + o(\mu_{ijt}^2). \tag{A.4}$$

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

$$\underset{N_j \to \infty}{plim} \left[\sum_{i=1}^{N_j} \frac{\mu_{ijt}^2}{N_j}\right] = \sigma_C^2. \tag{A.5}$$

Combining the equations in (A.3) and (A.4) and then (A.5), we proceed to estimate

the slope coefficient of G as

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

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

However, if there is a fixed effect in the model (A.1), we can proceed as follows:

(1) If there is an individual fixed effect and it's controlled for in the panel regression of model (A.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

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

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

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

(2) If there is a city (province) fixed effect and it's controlled for in the panel regression of model (A.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 $\tilde{\mu}^2_{ijt} = \mu^2_{ijt} - \frac{1}{TN_j}\sum_{x=1}^{T}\sum_{z=1}^{N_j} \mu^2_{zjx}$. According to (A.5), we can infer

$$\sum_{i=1}^{N_j} \tilde{\mu}_{ijt} = \sum_{i=1}^{N_j} \mu_{ijt} = 0, \tag{A.9}$$

$$\underset{N_j \to \infty}{plim} \left[\sum_{i=1}^{N_j} \frac{\tilde{\mu}^2_{ijt}}{N_j}\right] = \underset{N_j \to \infty}{plim} \left[\sum_{i=1}^{N_j} \frac{\mu^2_{ijt} - \sigma^2_C}{N_j}\right] = 0. \tag{A.10}$$

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

(3) If there is a time fixed effect and it's controlled for in the panel regression of model (A.1), then the equivalent $\tilde{G}_{ijt} = G_{ijt} - \frac{\sum_{y=1}^{K}\sum_{z=1}^{N_y} G_{zyt}}{\sum_{y=1}^{K} N_y} = G_{jt} - \frac{\sum_{y=1}^{K} N_y G_{yt}}{\sum_{y=1}^{K} N_y}$, 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 $\tilde{\mu}^2_{ijt} = \mu^2_{ijt} - \frac{\sum_{y=1}^{K}\sum_{z=1}^{N_y} \mu^2_{zyt}}{\sum_{y=1}^{K} N_y}$. According to (A.5), we can infer

$$\sum_{i=1}^{N_j} \tilde{\mu}_{ijt} = \sum_{i=1}^{N_j} \mu_{ijt} = 0, \tag{A.11}$$

$$\underset{min\{N_j\} \to \infty}{plim} \left[\sum_{i=1}^{N_j} \frac{\tilde{\mu}^2_{ijt}}{N_j}\right] = \underset{min\{N_j\} \to \infty}{plim} \left[\sum_{i=1}^{N_j} \frac{\mu^2_{ijt} - \sigma^2_C}{N_j}\right] = 0. \tag{A.12}$$

Similar to (A.6) and combining (A.11) and (A.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 (A.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 the individual fixed effect, the city (province) fixed effect, or the time fixed effect.

□