Real Life Experience and Financial Risk Taking:
Natural Experiment Evidence from Automobile Traffic Accidents[1]

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ABSTRACT

Utilizing records on automobile accident insurance filing and retail investor investment activities, we show that investors trade less, trade less aggressively, hold more diversified and less risky portfolios, and obtain relatively better returns, after experiencing automobile accidents. Such patterns are particularly strong for those suffer personal injury and above-average financial damage from the accidents. Our paper is among the first to provide direct evidence on the causal relationship between real life risk events and investors' risk preference in investment. Our findings contribute to the literature on risk preference, investor behavior, and equity risk premium.

Risk preference is an important determinant of many human behavior and personal choices. Extant literature shows that risk preference may have important impact on decision making in many aspects of life, such as health care, life style, and entrepreneurship and career development (Anderson and Mellor (2008), Choi et al. (2007), Dohmen and el. (2011), among others). In particular, there is a long standing literature that financial decision and investment is highly sensitive to investors' risk preference (Cohn et al. (1975), Slovic, (1972)). Therefore, understanding investor risk preference may be very important to answer important research questions such as equity market participation, asset allocation, and eventually asset price formation.

However, there is limited evidence on the possible relationship between risk preference in financial investment and real life risk experience. On one hand, traditional financial theories assume that financial decision making should focus rather narrowly defined risks, such as the volatility of security returns. Real life risk considerations, instead, take into account of a wider range of factors. On the other hand, it is plausible that certain common factors may drive real life risk preference and financial risk preference in a similar fashion and therefore there are some connection and spillover from one to another.

Portfolio choice and investment decision provide an arguably ideal backdrop for studying this problem, given that one can observe how investors choose securities with different expected risks and returns and adjust their portfolio choices as a result of shifting risk preference resulting from external shocks. For example, Melmandier and Nagel (2011), show that early life experience with the great depression has significant and long lasting impact on investors' equity market participation and portfolio asset allocation.

Despite its importance, field study evidence remains limited, largely due to data limitation. Whereas there is now increasing data availability and research literature on investor behavior, there are less opportunities to observe risk preference shifts in real life. Further, it is often challenging to disentangle risk investors' risk preference shifts in real life and in investment, let alone to precisely identify the causality of the relationship. Without clean exogenous shocks, such identification challenges hinder the literature from accurately understanding the mechanism of how risk preference percolates between investment and real life.

The current study utilizes unique data on investor behavior before and after automobile traffic accidents to study how financial risk taking shifts around real life risk events. Because we can precisely identify the timing and nature of exogenous traffic accidents in a relatively narrow window, we can control unobserved investor-level characteristics (such as genetic differences, prior life experiences, and unexpected wealth change, etc.) and macro-economic and market level shocks. Consequently, we can establish clear causal relationship between exogenous rea life shocks and financial risk taking before and after traffic accidents.

We find clear evidence that investors' real life risk exposure has significant impact on their financial risk taking and investors display significantly lower risk preference in investment after experiencing traffic accidents.

Sample investors trade far less frequently after the accidents. For the 30-day window period around accidents, investor purchase turnover decreases from 17.31 percent to 9.81 percent (a 43.3 percent reduction), and sale turnover decreases from 14.97 percent to 7.91 percent (a 47.2 percent reduction). Put together, investor overall turnover decrease from 32.38 percent before the accident to 17.72 percent after the accident (a 45.1 percent decrease). Such changes are economically considerable and highly statistically significant. Despite the decrease in investors' trading frequency, the number of unique stocks that investors transacted indeed increased from 3.01 unique stocks to 3.96 unique stocks, a 31.6 percent increase after the traffic accident, suggesting increasing inclination for diversification.

At the same time, the risk profiles of sample investors' purchases and portfolio holdings also shift around accidents. For example, the fraction of SME stocks reduced from 16.83 percent to 16.81 percent of investor portfolios, the fraction of ChiNext stocks reduced from 5.15 percent to 5.01 percent, and the fraction ST stocks reduced from 0.82 percent to 0.78 percent, from the one-month period before traffic accidents to the one-month period after the accidents. Given that SME stocks, ChiNext Stocks and ST stocks are all proxies for riskier stocks, our findings suggest that experiencing traffic accidents has brought meaningful changes to how investors perceive risks in finance and risk seeking behavior in their equity market investment.

In addition, we show that investors' reduced trading intensity and shifting risk attitude result in improved investment performance. The purchase transactions by sample investors return -0.057 percent after the traffic accidents, which is 0.17 percentage higher than the alpha of the portfolios following the same investors' purchase decisions before the accidents (-0.074). On the other hand, the alpha of the portfolio of sample investors' sale transactions after accidents is -0.044 percent, which is 0.003 percentage higher than the alpha of the portfolio of sample investors' sale transactions before the accidents (-0.041). Taken together, the alpha of a portfolio that long stocks picked by sample investors and short stocks sold by sample investors reports an alpha of -0.013 percent after the accidents, 0.02 percentage higher than the alpha of the portfolio following the same strategy before the accidents (-0.033 percent). Such results provide strong support that sample investors obtain significantly higher returns after experiencing traffic accidents. Consistent with previous findings, our calendar-time portfolio approach confirm that investors tend to tilt their purchases toward stocks with larger market capitalization and lower valuations, again proxies for less risky stocks, after experiencing traffic accidents.

Finally, we show that investors experiencing bodily injury and greater financial damage in the accidents, two clear proxies for greater risk exposure in real life accidents, display much stronger change in their financial risk taking and equity investment performance. Such findings provide additional support for our argument that real life risk experience influences investors' financial risk preference and trading behavior.

A host of robustness tests with sub-samples of different regions, different types of insurance policies, different involved parties, and different investor characteristics generate highly consistent results to our main findings.

Our findings contribute primarily to the following two strands of the literature. First, we provide one of the first evidence on how real life experience affects risk preference and financial risk taking. Risk taking is considered as one of the most important aspect of decisions in the financial market (Sapienza, Zingales, and Maestripieri (2009)) and used as explanations for many real life decisions (Barsky et al. (1997)). Despite the increasing speculation that the risk taking decisions may not be independently determined as commonly assumed in many theoretical studies, there is little evidence about how exposure to risky events in one aspect of life may affect risk taking in other aspects of life such as financial decisions.

On one hand, it is conceivable that financial decisions may be compartmentized as a separate process under 'mental accounting' (Thaler (1999)). On the other hand, some extant studies indicate that life experience (through dramatic market volatilities) may indeed have profound and long lasting impact on individual's financial taking (Malmendier and Nagel (2011)). The current study distinguishes from Malmendier and Nagel (2011) in several significant ways. First, unlike their study that focuses on how past life experience of macro-level economic conditions (such as economic growth speed, inflation, and capital market performance) influences individuals' subsequent portfolio choices, we present more direct and immediate implications of how micro-level risk-exposure in real life affects investors risk preference and portfolio at individual investor level. In addition our natural experiment set up can clearly identify the causality of the impact and also delineate the precise nature of the individual-level shift in risk preference. Finally, in addition to their findings on long term shift of asset allocation, we provide additional evidence on how short term trading behavior in response to external risk profile as well.

The current findings provide field study support to experimental findings (Callen, et al. (2014)) that, in contrast with the assumption of constant risk preference and utility functions for the same individual, individuals' utility function and risk preference in decision making may indeed be dynamic and susceptible to risk exposure and external environment over time. Further, we show that previous evidence of how experience of long-term macro events affects investors' decision may indeed stem from their shifting risk preference, instead of simply varying expectations of future returns (Shiller (2000)).

Second, our findings contribute to the growing literature on investor behavior and its impact on asset prices. It has become widely accepted that investors often make sub-optimal investment decisions and such behavioral mistakes may have considerable impact on formation of asset prices (Barber, Odean, and Zhu (2008), Kumar and Lee (2006) and Hvidjaker (2008)). Our findings provide an additional mechanism through which investors, especially retail investors' decisions deviate from the optimal decisions predicted by finance theory. In addition to increasing evidence showing how investors' decisions are affected by genetic differences in risk preferences (Grinblatt and Keloharju (2009) and Cesarini et al. (2010)) and familiarity with different sets of information and investment opportunities (Seasholes and Zhu (2010) and Huberman (2001)), our paper shows that investors' consideration and risk preference can also change in reaction to real life experience outside the investment context. Such findings stress the complexity of investment decision making in real life and the need to incorporate a wider range of factors into understanding investment behavior and its impact on asset price formation and market volatility.

The rest of the paper proceeds as follows: Section 2 outlines the background of China's automobile industry and the process related to automobile accident insurance; Section 3 describes our data on automobile accidents and investor investment behavior; Section 4 presents results on the contrast between investors' investment behavior before and after traffic accidents; Section 5 discusses our results before concludes.

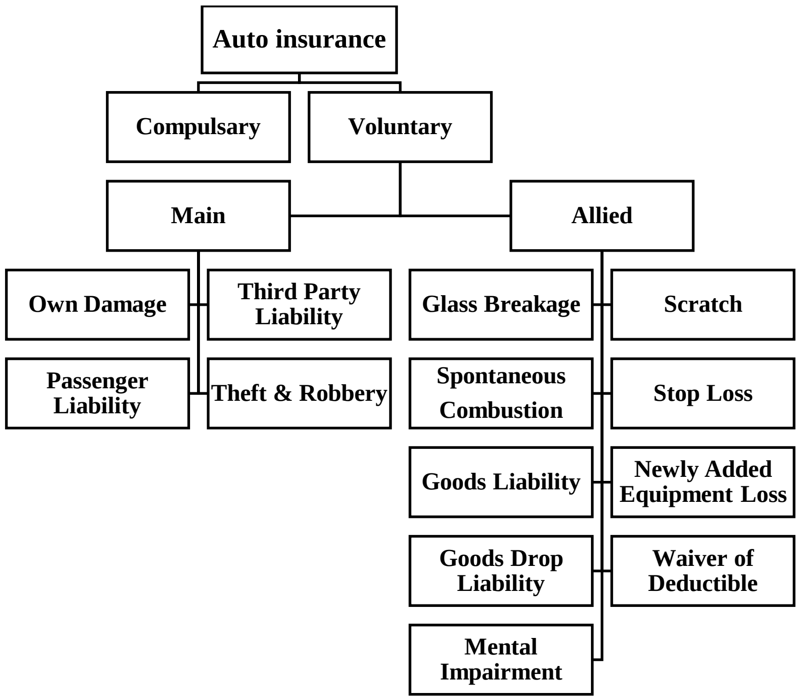
2. Background: China's automobile industry and related insurance

China has the largest population in the world of over 1.3 billion and the fourth largest automobile insurance market in 2015. According to official statistics[2], China's car ownership reaches 304 million in 2015, among which 291 million are covered by the insurance industry. From an insurance industry perspective, in 2015, the original premium income of China's property insurance companies reached 735.51 billion RMB, of which 619.9 billion RMB came from auto insurance.

Compulsory Traffic Accident Liability Auto Insurance and Voluntary Commercial Auto Insurance are two main product categories in China's auto insurance market. All automobile drivers are required to have compulsory traffic accident liability (CTAL), which covers basic healthcare and third-party policies. The Voluntary Commercial Auto Insurance (VCAL) primarily includes Own automobile damage, third party and passenger liabilities, and theft & robbery

[2] Data comes from Yearbook of China's Insurance (2016) and China Statistical Yearbook (2016).

coverage. The covered causes mainly include glass breakage, stop loss, accidental combustion, water damage, and waiver of deductible.



The automobile insurance in China has been operating under the government's strict regulations for several decades. China Insurance Regulatory Commission (CIRC) gives the market strict premium rate regulations.

In 2006, China Insurance Regulatory Commission (CIRC) conducted a reform on auto insurance rates and introduced Compulsory Traffic Accident Liability Auto Insurance. The Insurance Association of China (IAC) formulated the basic auto insurance rates into A, B and C standards and required insurance companies choose one of the three for implementation while allowing for autonomic rates in allied perils. In 2007, IAC promulgated unified rates for terms commonly appeared in allied perils, followed by CIRC's order which limits the maximum discount for an auto insurance policy to 30%. These policies highlight the uniformity, legality and riskpreventing characteristics of auto insurance rates, which aim to curb malignant price competition in the auto insurance market and promote insurance companies to improve profitability. Under these rules, the auto insurance rate is priced based on the "insured amount", that is, if two cars have the same price, the insured amount and the premium rate is basically the same, while very few considerations are given to the effects of vehicle models, let alone taking into account the man-made factors.

From June 2015, China initiated a new wave of reform on auto insurance rate which was firstly piloted in 18 regions and then promoted nationwide from July 2016, aiming at expanding the pricing autonomy of insurance companies for commercial auto insurance rates. The basic premium is priced based on car model rather than the insured amount, taking into account risks on safety factor and maintenance costs generated from various vehicle models. In terms of experience premium, self-underwriting factor and traffic violation factor are added to the original no-claim discount factor (determined by the number of loss occurred) and the last-year payment records factor.

Although these reforms granted insurance companies more pricing autonomy and promoted market competition with an overall decline of the premium rate, the oligopoly structure in China's insurance market had not been changed significantly in the short run. Data from the first half of 2016 shows that the total share of top three property insurance companies PICC, Ping An and CPIC still take up about 66% of China's property insurance market.

3. Data and Methodology

3.1. Data on automobile traffic accidents

Our data come from two distinct sources. We obtain information for automobile traffic accidents from the automobile insurance database of the Chinese Insurance Information Technology Company (CIITC), a state-owned agency that compiles and manages complete China's insurance market information data based on information submitted by all the insurance companies in China as required by the mandatory information provision by China Insurance Regulatory Commission (CIRC).

For the year of 2015, we obtain complete traffic accidents from ten provinces in China. These provinces not only claim a large share of China's economy and population (59.85 percent of China's GDP as of 2015), but also a large fraction of China's automobile ownership (60.15 percent of China automobile ownership) and 56.62 percent of insurance premium (56.72 percent of property insurance contracts). Unlike previous studies that rely on data reported by certain insurance companies or random samples, our data includes complete information on all traffic accidents in sample year within respective region and ensures representativeness and accuracy.

In order to obtain as comprehensive data as possible, we focus on all accidents that took place in 2015, which have completed their claim and remuneration within 2015. This requirement necessary as this provides the complete information on the property damage of the accidents, which helps us assess the extent to which the accidents may bring shock to the insured.[3] In addition, we only focus accidents major enough to have potential impact on investors' financial risk taking and investment behavior. In particular, we limit our sample to those where property damage is greater than the median (1,250 RMB) of all accidents in our sample or there is involved bodily injury. Our unreported analysis confirm that we obtain qualitatively consistent results if we apply alternative criteria in forming our final sample.

For each accident, we have information on the date and time of the accidents, the property

[3] By utilizing an alternative data sources, we confirm that that cases completed within a calendar year are representative of all accidents in 86.32%.

value loss caused by the accidents, whether there was bodily injury involved in the accidents, and IDs of corresponding policy holders, policy purchasers, and drivers.

(Insert Table 1 about here)

As Table 1 reveals, there are a total of 16,425,210 traffic accidents filed under collision policy, 5,810,630 traffic accidents filed under third party policy, and 3,015,601 accidents involved personal injury or casualty. As to the profile of the people involved in the traffic accidents, their average age is 38 for people filed under the collision policy and 39 for those filed under third party collision.

Geographically, Guangdong, Jiangsu, and Shandong provinces register the largest number of people involved in traffic accidents, with 2,810,436 2,023,514, 1,634,278 accidents filed under the collision policy respectively within each province. This pattern is largely consistent with the population distribution across these provinces. We also calculate the proportion of accident to population and the ratio is largely similar ranges from 0.6% to 2.6% across different provinces.

There are some differences the gender distribution for those involved in the accident under difference types of policies. Under the collision policy, 72.21 percent of the people involved are male whereas the proportion is slightly higher of 80.01 percent for the third party policy and much smaller of 34.65 for the third party policy.

3.2. Data on investment behavior

Information on investors' transaction and holdings data come from a large national brokerage firm in China. The company has branches in almost all of China's provincial-districts and are market leaders in several of such areas.

We have complete transaction records for all investors with active trading activities in the year of 2015. In addition, we also obtain complete portfolio holdings data of year 2015 for all investors. Combined, the transaction and holdings data provides a comprehensive depiction of each investor's investment activities.[4]

We present summary statistics about our brokerage data in Table 2. The brokerage sample includes 2,388,187 investors. These investors on average make 96 trades (median is 93) with an annualized turnover of 1203% (median is 1173%). Such findings are consistent with the extant literature that retail investors trade excessively in Chinese A Shares market. The average age of sample broker investor is 38 and consistent with insurance sample investors and 53 percent of sample retail investors are male.

(Insert Table 2 about here)

3.3. Final sample

For the purpose of investigating investor behavior shift around automobile, we match the insurance company data with the one from the large brokerage firm and obtain information on automobile accidents and investment activities around the events for a sample of 60,481 investors involved in various types of automobile accidents.[5] Within these 60,481 investors, 58,505 and

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[4] Chinese retail investors are allowed to open only one brokerage account with one brokerage firm for all its trading activities in the A-shares market before 2015 (April 13, 2015). Although households are allowed to open multiple accounts after April 13, 2015, survey (China Household Finance Survey by China Southwestern University of Finance and Economics) indicates that it is very limited that one has multiple brokerage accounts in 2015.

[5] We match the brokerage data with the automobile insurance data by the people involved in the accidents. This matching method gives us the largest number of matched sample of 60,481 investors. We have experimented alternative matching method of matching between the retail investor data and the insured and third party. These alternative matching method generates a

20,238 were filed under collision policy and third party policy respectively, and 5,638 people were involved in personal injury and casualty. For the sake of presentation simplicity, we report our main results based

3.8 percent of brokerage investors match in the insurance dataset, which mirrors well with the accident rate for the entire sample of the insurance dataset. A comparison of the matched sample with the entire sample of investor activities reveal that the investors in our final sample provides a fairly representative sample of investment activities for the whole sample of retail investors. On average, investors in our final sample made 244 trades in 2015 (138 buys and 106sales), compared to the whole sample average of 96 trades (58 buys and 38sales).[6] These trades on average involve 37 unique stocks. Despite the more frequent trading compared to the whole sample, the average value of our final sample investors is 288,556.24, close the average value of whole sample retail investors (280,368.25).

(Insert Table 3 about here)

At the same time, in unreported additional analyses, we find that accidents in our final sample are similar to the whole sample of traffic accidents in the average damage value, the percentage of bodily injury, and the length of processing time. Above results confirm that our final matched sample provides a fairly reliable representation of the entire insurance industry and retail investor universe.

sample of 58,505 and 4,224 investors and generate consistent results with our main findings. Such findings are available upon request.

[6] This is because the whole sample includes many accounts from inactive investors who do not trade much during the sample period.

4. Hypothesis development

Following the extant literature in psychology and insurance, we hypothesize that experiencing traffic accidents may shift investors' risk preference. If this change in investors' risk preference is also reflected in investors' investment behavior, we expect investors to become less tolerant of risks and trade less aggressively. Given that investors' excessive trading is related to investors' over-confident and mis-judgment of risks, we hypothesize that a lower level of risk tolerance will lead investors to trade less and frequently and less speculatively. In addition, we expect investors to trade less aggressively after traffic accidents and one way to proxy for the shift in investors' transaction riskiness is the unique number of stocks, industries, and sector concentration. A higher level of concentration if often used as a proxy for higher level of confidence or lower level of risk aversion.

In particular, we form the following hypothesis:

Hypothesis 1. Investors trade less frequently after suffering from traffic accidents

Odean (1999), Barber and Odean (2000) show that retail investors trade too frequently and such excessive trading can be largely explained by investors' over-confidence with their own investment ability or private information. As we argue earlier, if there is a spillover from investors' real life risk perception and risk aversion to the risk aversion in their financial decision making, we expect investors' risk preference in financial decision making to diminish after personally experiencing traffic accidents. Such a drop in one's risk preference could have two potential impact on investors' decision. One, the incidents may affect how investors assess their own driving abilities and possibly investment abilities and such an adjustment in one's assessment of one's ability may lead investors to display a lower level of over-confidence and lower inclination to trade stocks.

At the same time, it is conceivable that even if one's level of confidence were not to be changed after the accidents, one's risk preference may reduce and therefore, display a lower level of enthusiasm with investing or speculating in the stock market.

It is not the intention of this paper to disentangle which precise mechanism has greater influence on investor's changing trading behavior we focus more narrowly on how investors' trading intensity shifts after traffic accidents and expect investors to trade less frequently after experiencing personal risk events.

Hypothesis 2. Investors buy a large number of unique stocks, large number of sectors.

Extant studies show that retail investors tend to trade stocks concentrated in particular geographical areas or industrial sectors, partly due to investors' perceived familiarity with a particular sector of the market. In addition, retail investors are also known to have the tendency to repurchase the stocks which they have previously sold, partly due to familiarity and partly due to confirmation bias. Similar to our above argument, if an investors' self-assessment of ability or risk preference changes after experiencing traffic accidents, she would probably display a lower level of risk preference or over-confidence. That may be reflected by an increase in the number of unique stocks that she buys, because purchase decisions are initiated after the accidents whereas sale decisions may be partly influenced by what the investor already holds in her portfolios

Hypothesis 3. Investors' transactions display a lower level of sector concentration after accidents

Extant studies show that investors with different sophistication and characteristics prefer to invest in different types of stocks. For example, Kumar (2009) show that less sophisticated retail investors prefer riskier and lottery-like stocks. Following such arguments, we expect investors to purchase less risky stocks such as stocks with large market capitalization and stocks with relatively low valuation

Hypothesis 4. Investors will tilt their purchase toward stocks with lower risk profile.

Further, we expect that after the accidents, investors become more risk averse and more careful with their financial decision making. This change in risk preference will lead investors to be less over-confident with their private signals and trade less speculatively. As a result, we expect investors to obtain better investment performance after experiencing traffic accidents.

Hypothesis 5. Investors obtain better investment performance after accidents.

A large strand of literature on investor behavior documents that retail investors typically under-perform the stock market benchmark, due to mistakes such as excessive trading, over-extrapolation, and under-diversification.

Part of such under-performance stems from the fact that investors cannot fully or accurately assess the risks associated with the stocks that they decide to purchase and unwilling to realize their losses when such losses emerge.

Following this line of reasoning, if there is indeed spillover from real life risk preference to risk preference in financial investment, traffic accidents should probably reduce investors' risk preference and trading activities. Given that a large fraction of retail investor trading is motivated by investors' over-confidence and behavioral biases, we expect the reduction in investors' speculative trading to lead to improvement in retail investors' investment performance after experiencing accidents.

4. Methodology and empirical findings

Our empirical design is straightforward. We summarize each investor's investment trading activities and portfolio characteristics before and after the investor experienced traffic accidents and focus on the difference for the within-investor change in investors trading activities, portfolio characteristics, and investment performance.

4.1. Changes in Investor Trading Activities

On investor trading activities, we focus on the following four aspects: the number of trades, transaction turnover, the number of unique of stocks traded, and the riskiness of the stocks traded, the degree of diversifications for the purchased.

We first report the change in turnover by investors before and after accidents. As previous studies (Barber and Odean (2000) and Barber, Odean, and Zhu (2008)) show, trading activities reflect investors' overconfidence and sensation seeking tendency, which is probably highly correlated with investors' risk preference. The results in Table 4 suggest that that the number and dollar value of investor trades also decrease significantly after traffic accidents. In particular, the number purchase transactions decrease from 0.76 before the accident (which means that investors on average executed 0.76 purchase transactions during the one-month period prior to the accident) to 0.59 afterwards (which means that investors on average executive 0.59 purchase transactions after the accident). Similarly, the number of sale transactions decreases from 0.59 before the accident to 0.45 afterwards. Taken together, sample investors performed a total of 1.35 trades before the accidents and 1.03 afterwards. The decrease in purchase, sale, and total number of transactions are all highly statistically significant and represent a 22, 24, and 23 percent decrease from their base case before the accidents, respectively.

(Insert Table 4 about here)

We next examine the difference in trading activities in the longer 3-month window period and our results remain largely the same. In particular, the number purchase transactions decrease from 0.62 before the accident (which means that investors on average executed 0.62 purchase transactions during the two-month period prior to the accident) to 0.56 afterwards (which means that investors on average executive 0.56 purchase transactions after the accident). Similarly, the number of sale transactions decreases from 0.47 before the accident to 0.42 afterwards. Taken together, sample investors performed a total of 1.08 trades before the accidents and 0.98 afterwards. The decrease in purchase, sale, and total number of transactions are all highly statistically significant and represent a 9.36, 10.24, and 9.74 percent decrease from their base case before the accidents, respectively. We further investigate even longer 6-month window period and find consistent albeit weaker results which confirm that the shocks of the traffic accidents are indeed long lasting and gradually wear off over time.

Our comparison of number of transactions before and after the accidents provide some more intuitive exposition of the changes in trading activities after the traffic accidents. Despite that we perform investor-based pairwise comparison of investors' number of transactions, turnover is a more accurate description of the precise change of investor trading tendency around the accidents.

If the change in investors' trading intensity is indeed influenced by a change in their risk preference, we expect that investors' transaction turnover to decrease after the accidents This is exactly what we have found in the Table 4. For the 30-day window period, investor purchase turnover decreases from 17.31 percent to 9.81 percent (a 43.3 percent reduction), and sale turnover decreases from 14.97 percent to 7.91 percent (a 47.2 percent reduction). Put together, investor overall turnover decrease from 32.38 percent before the accident to 17.72 percent after the accident (a 45.1 percent decrease).

For the 60-day window period, investor purchase turnover decreases from 12.95 percent to 9.70 percent (a 25.1 percent reduction), and sale turnover decreases from 10.68 percent to 7.57 percent (a 29.1 percent reduction). Put together, investor overall turnover decrease from 23.63 percent before the accident to 17.67 percent after the accident (a 26.9 percent decrease). Again, the longer term six-month window period report qualitatively consistent yet quantitatively weaker results which are available upon request.

Such findings confirm previous findings on the number of transactions in that investors significantly and substantially reduce the number of trading intensity after the traffic accident.

Interestingly, we notice that despite the decrease in investors' transaction number and turnover, the number of unique stocks that investors transacted indeed increased from 3.01 unique stocks to

3.96 unique stocks, a 31.6 percent increase after the traffic accident. Such results suggest that, consistent with our hypothesis, the real life experience of traffic accidents, can probably lead to a lower level of risk preference, which can be reflected in both the reduction in the number of transactions and the simultaneous increase in the number of unique stocks, as more diversified choice of stocks and portfolio holdings also reflect a decreased level of risk preference probably resulting from the traffic accidents.

Our findings on the changes in the unique number of stocks that investors transact also provide some interesting evidence that can help distinguish our hypothesis of risk preference shift from an alternative hypothesis that the reduction in investors' trading intensity is caused by the psychological shock that investors experienced from the accident or the distractions that investors experience from handling accident-related matters. If the above competing hypotheses are true, we should observe a simultaneous reduction in the number of transactions AND the reduction in the number of unique stocks as a result of reduced time and energy spent on investment related tasks. Instead, our findings of reduced transaction YET increased number of unique stocks seem to confirm that reduced risk preference after experiencing traffic accident is a more likely explanation. Consistent with such an argument, we also find that the number of unique industries that investor purchased also increases in unreported analyses, further supporting our argument that risk preference shift is responsible for changes in investors' behavior.

This may reflect two possible changes. First, investors become more risk averse and therefore choose to further diversify their portfolio. At the same time, the accidents alerted investors to pay attention to certain areas of the economy or sectors of their portfolio (i.e. insurance industry and safety industry). As a result, the investors decide to favor certain previously ignored sectors and diversify their portfolios to reflect such shift in their preference. We will next investigate the characteristics of investors' trading and portfolio holdings to further explore potential drivers behind the shift in the diversification of investors' trading and portfolio holdings.

4.2. Changes in Transaction and Portfolio characteristics

Our findings in the previous section suggest that investors reduce their number of transactions and increase the number of unique stocks after experiencing traffic accidents. Extant literature shows that risk preference not only affects investors' tendency to trade, but also the type of securities that they choose and the consequent investment returns. Malmendier and Nagel (2011), for example, show that personal experience with the great depression period has long lasting influence on an investors' likelihood to participate in the equities market and asset allocation decisions. Grinblatt and Keloharju (2009), in addition, show that investors with greater likelihood to seek sensation are more likely to invest in riskier stocks.

If the change of investment behavior after traffic accidents are largely driven by shifts in risk preference as we argue, we expect that investors to change not only the number of stocks or the number of industry sectors that they trade, but also more broadly the type of stocks that they decide to invest in. Put differently, investors experiencing traffic accidents would probably develop lower risk preference and therefore should probably invest in less risky stocks than they used to.

This is exactly what we have found in Table 5. We first calculate the fraction of stocks listed at the Small and Medium Enterprise (SME) board, listed the fraction of ChiNext board, and facing special treatment (ST) sanctions in investors' portfolio before and after the accidents as one way to illustrate the contrast in the riskiness in investors' portfolios.

(Insert Table 5 about here)

Because the SME board lists younger companies and companies with relatively smaller market capitalization, it is widely believed that SME stocks are riskier than those listed at the mainboard. ChiNext, China's counterpart to NASDAQ, was established to encourage early-stage enterprise and sets even lower listing requirement for profitability and asset size than the SME board, and is therefore regarded to list some even more riskier stocks than the SME board. Special treatment (ST) sanction applies to stocks which have been reporting operating losses for the past three consecutive years and ST stocks are therefore considered highly risky given their uncertain future and realistic possibility of being delisted.

We show that the fraction of SME stocks reduced from 16.83 percent to 16.81 percent of investor portfolios, ChiNext stocks holdings reduced from 5.15 percent to 5.01 percent, and ST stocks holdings reduced from 0.82 percent to 0.78 percent, from the one-month period before traffic accidents to the one-month period after the accidents. All results are highly significant by conventional statistical standard. Such findings provide additional support that, not only do investors trade in a less risk-seeking way, their choice of stocks after traffic accidents has also shifted towards less risky stocks.

In addition, we calculate the average market capitalization, the book-to-market ratio for investors' portfolios before and after the accidents. Again consistent with our hypothesis on risk preference change, we find that the average of the logarithm of company market-adjusted market capitalization increases from 7.27 to 7.33, suggesting that investors are more likely to buy and hold companies with relatively larger market capitalization. At the same time, the average of the average of the logarithm of company market-adjusted book-to-market ratio increases from -0.381 to -0.379, suggesting that investors are more likely to hold stocks with relatively lower valuation after the traffic accidents.

Our findings thus confirm our preliminary results based on the number of unique stocks and unique industry sectors and confirm that investors indeed prefer stocks with lower risk profiles after experiencing traffic accidents, lending further support to our main hypothesis.

Reflecting the changes brought forward to investors' trading activities, investors' portfolio's riskiness and degree of diversification are likely to change accordingly around traffic accidents. To confirm such conjectures, we perform further analysis by comparing the characteristics of the portfolio holdings held by sample investors before and after they experience traffic accidents.

We show in Table 5 that the investors' holdings of stocks listed at Small and Medium Enterprise Board (SME Board), the ChiNext Board, and stocks facing the Special Treatment (ST), all proxies for higher risky investment choices, all decrease significantly after investors experience traffic accidents. In addition, sample investors' portfolio holdings tilt toward stocks with relatively larger market capitalization, stocks with relatively lower valuation, and stocks with relatively lower idiosyncratic volatilities, lending further support to our hypothesis and previous trading-based results that investors display significantly lower risk preference, as reflected by an apparent decrease in the riskiness of their trading decisions and portfolio holdings.

4.3. Portfolio Performance

Further, various studies show that retail investors make systematic mistakes in their trading decision and portfolio choices and suffer performance significantly below that of respective market benchmarks (Odean (1999)). Part of such under-performance can be attributed to investors' excessive trading, caused by investors' over confidence of their information and risk management (Odean (1998)). As we show that investors become more careful with risk taking after experiencing traffic accidents, it is plausible that their portfolio performance may improve consequently.

Following the above rationale, we next focus on the portfolio performance and characteristics around traffic accidents. Based on our previous findings drawing from the shift in investors' trading decisions, we expect that the portfolio composition and hence performance will change accordingly, after experiencing traffic accidents. If real life experience indeed brings changes to an investors' risk preference, we expect to find that investors shift to invest less in riskier stocks and less speculative fashion, both of which are expected to contribute to an improvement in investment performance (Barber and Odean (2001)).

Here, we take two different approach to assess investor performance before and after traffic accidents. First, we adopt the calendar-time portfolio approach to evaluate the performance of all transactions executed by retail investors around the events. In particular, we expect that investors make relatively better purchase (which generate better post-purchase returns) after traffic accidents than those before the accidents. Such an approach not only allows us to track the respective performance of the stocks that investors choose to buy and sell around the events, but also enable us to investigate potential changes in the characteristics of the stocks that investors choose to transact. (see Seashles and Zhu (2010) for details)

Secondly, we follow Barber and Odean (2001) by calculating self-benchmark performance by comparing the relative performance of investors' portfolio holdings after the accident with that of investors' portfolio holdings before the accident, in order to trace the impact on performance caused by the trades that investors executed after experiencing traffic accidents. That is, we intend to compare the investors' performance after the accidents, with their counterfactual performance if they had not been involved in the traffic accidents. Given that most Chinese investors' portfolios are highly concentrated, the change in investors' choice of stocks to purchase should have noticeable influence on the portfolio composition and performance after the accidents.

We start by presenting results from calendar-time portfolio analysis. We report all of our results based on the holding period of one month. We choose the one-month holding period assumption because Chinese A-shares investors trade actively and have high portfolio turnovers. We calculate the average holding period for our sample retain investors. For the 11.28% of purchase trades that are liquidated in the same number of shares as the number of purchase, the average number of holding days is 16.89 (median is 4). We cannot accurately estimate the average holding period for those remaining 88.72 percent trades that are not liquidated in the same number as purchase or not liquidated at all during our sample period. Our alternative approach of assuming two-week, two-month, and three month holding periods generate qualitatively consistent results.

We show in Panel A of Table 6 that similar to the findings in other equities market (Barber and Odean (2000)), our sample retail investors significantly under-perform market index. The sample investors' purchase trades generate -0.057 percent characteristics-adjusted returns (alpha) and investors' sales trades generate -0.041 percent characteristics-based returns (alpha). Similar to extant research, the sample investors' purchase trades under-perform their sales trades, which under-perform benchmark. The buy-minus-low strategy following retail investors' transactions therefore generate an average of -0.033 percent (-8.41 percentage annualized) characteristics-based returns.

(Insert Table 6 and 7 about here)

When we compare investors' performance before and after experiencing the traffic accidents, a distinct pattern emerges that sample investors' performance is significantly better after suffering from the traffic accidents.

For example, we show that the purchase transactions by sample investors return -0.057 percent after the traffic accidents, which is 0.17 percentage higher than the alpha of the portfolios following the same investors' purchase decisions before their respective accident (-0.074). On the other hand, the alpha of the portfolio of sample investors' sale transactions after accidents is -0.044 percent, which is 0.003 percentage higher than the alpha of the portfolio of sample investors' sale transactions before accidents (-0.041). Taken together, the alpha of a portfolio that long stocks picked by sample investors and short sell stocks stock by sample investors reports an alpha of -0.013 percent after the accidents, 0.02 percentage higher than the alpha of the portfolio following the same strategy before the accidents (-0.033). Such results provide strong support that sample investors obtain significantly higher returns after experiencing traffic accidents. Nevertheless, consistent with extant studies, sample investors' improved performance still significantly under-performs market benchmark.

Further, our value-weighted results report qualitatively consistent and statistically weaker results. The purchase transactions by sample investors return -0.053 percent after the traffic accidents, which is 0.03 percentage higher than the alpha of the portfolios following the same investors' purchase decisions before their respective accident (-0.056). Similarly, the alpha of the portfolio of sample investors' sale transactions after accidents is -0.048 percent, is 0.01 percentage lower than the alpha of the portfolio of sample investors' sale transactions before accidents (-0.038 percent). More to the focus of the paper, the alpha of a portfolio that long stocks picked by sample investors and short sell stocks stock by sample investors reports an alpha of 0.01 percent after the accidents, 0.013 percentage higher than the alpha of the portfolio following the same strategy before the accidents (-0.003), which translates into 3.4 percentage annualized returns.

In addition, our results in Panel A of Table 6 reveal that, not only does the sample investors' investment performance improved significantly after the traffic accidents, but also do they display a different preference in their choice of the stocks that they invested.

Although there is no noticeable difference between the betas of the two portfolios, the factor loadings of the SMB and HML factor are present a different and interesting pattern. For the SMB factor, the before-accident-portfolio coefficient is 0.517 whereas the after-accident-portfolio coefficient is 0.421, with the difference of 0.095 significant at the one percent level. That is, sample investors on average tilt their purchases towards stocks with small market capitalization and their preference for small stocks becomes weaker after the accidents. Given that stocks with small market capitalization are generally considered riskier than those with large market capitalization, our findings suggest that, consistent with our hypothesis, investors display weaker preference for risky stocks (smaller stocks) after traffic accidents.

Our results on the change in HML loadings reveal a similar pattern. For the HML factor, the before-accident-portfolio coefficient is -0.022 whereas the after-accident-portfolio coefficient is 0.013, with the difference of increase of 0.035, which is significant at the five percent level. That is, sample investors on average tilt their purchases towards high valuation stocks (low book-to-market ratio growth stocks) before experiencing traffic accidents and their preference for growth stocks shifts after experiencing traffic accidents and becomes slightly preferable of low valuation stocks (high book-to-market ratio growth stocks) after the accidents.

Further, we find consistent results when we compare the size and book-to-market characteristics of the mimicking portfolios that long the stocks bought by sample investors and short the stocks sold by sample investors, before and after the traffic accidents. We indeed find that the mimicking portfolio also display lower preference for small stocks and growth (low book-to-market ratio) stocks and such results are generally significant at the five percent level.

Given that growth (low book-to-market growth stocks) stocks are generally considered riskier than stocks with low valuation (high book-to-market ratio value stocks), our findings again show that investors display weaker preference for risky stocks (growth stocks) after traffic accidents. Our findings based on investors' holdings show that, consistent with our previous findings based on investors' transactions, sample investors' portfolio tilt more towards larger stocks and stocks with relatively lower valuation, again confirm our hypothesis that investors' risk preference decreases after experiencing risky traffic accidents in real life.[7]

We next present empirical findings based on self-benchmark analysis in (Barber and Odean (2000)). This approach compares the counterfactual portfolio returns should sample investors not have changed their portfolio holdings without experiencing the traffic accidents.

(Insert Table 8 and 9 about here)

We find that sample investors' real portfolio after traffic events generate significantly higher returns than their benchmark portfolios should there have not been changes to investors' portfolios. Such results are robust at the one-, three-, and six-month holding period and provide further support that the traffic accidents lead to improvement in sample investors' investment performance, partly because of investors increasing sense of risks and less rash investment decisions.

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[7] We also experiment with the 3-month and 6-month holding period and our results are highly consistent with our main findings.

4.4. Traffic damage and changes in risk preference

Now that we show investors display reduced level of risk preference in their financial investment after experiencing risky events in their personal lives, it is interesting to explore whether the nature and gravity of such accidents may have varying impact on the reduction in investors' risk preference in financial investment.

There are at least two dimension by which accidents vary in terms of their impact on investors' experience with the traffic accidents. First, some investors suffer from bodily injury during the accidents. According to the insurance literature (Cummins and Tennyson (1992)), bodily injuries cause greater drama and physical inconvenience and lasting impression of traffic accidents to those involved in the accidents. We therefore expect investors who suffer with bodily injuries from the traffic accidents to demonstrate a greater reduction in their risk preference.

We therefore divide the whole sample into two sub-samples: accidents that involve bodily injury and those that do not involve bodily injury. The results in Table 10 confirm that investors who have suffered from personal injuries display much stronger reduction in their preference than those who do not suffer from personal injuries. In particular, we find that the stocks purchased such a conjecture and our main findings. We show that the reduction in investors trading intensity, improvement in investment performance, and change in the riskiness of investors' transactions, are all stronger for investors who have experienced bodily injury.

(Insert Table 10 about here)

Second, even for those who do not suffer with bodily injury, it is conceivable that greater financial damages from the accidents would probably cause greater shock to investors and hence bigger change in their risk attitude. We therefore conjecture that those who suffer from accidents with greater financial damages tend to displayer a greater reduction in their risk preference in financial investment, than those who suffer from accidents with relatively smaller financial damages.

Following a similar logic, we divide the whole sample into two sub-sample of accidents that incur above-median financial damage and those that incur below-median financial damage. If our logic about the financial damage and investor risk aversion is valid, we expect to observe greater change in investor trading actions and performance for the sub-sample of accidents that incurred above-average financial damage.

This is exactly what we have found. The results in Table 11 show that the investors experiencing greater financial damage during traffic accidents change their investment risk taking far more substantially than those who suffer less damage. For example, investors suffer from greater financial damage tend to tilt their portfolios towards stocks with larger market capitalization whereas investors with less financial damage indeed tilt their portfolios towards stocks with smaller market capitalization, which is a widely used proxy for riskier stocks. Separately, investors with greater financial damage tilt their investment choices more towards stocks with lower valuation (value stocks) than those with less financial damage, again consistent with our conjecture.

(Insert Table 11 about here)

In unreported analyses, we also use the time lag between the traffic incidents and when full insurance payment is made as an alternative measure of the complexity and severity of the accidents and obtain very similar results.[8]

Our above findings again provide strong support to our main findings that real life experience with traffic accidents have significant impact on investors' risk preference in financial investment, as reflected by investor's trading activities and investment choices.

5. Robustness tests

We conduct a host of additional tests to verify the robustness of our main findings.

We first split our sample into the first half and second half of 2015 to test the robustness of our results within each sub-sample. This is particularly relevant for the year 2015 because the China A-shares market surged in the first half of the year and tumbled in the second half. It is interesting to see whether the market volatility has any influences on our results.

(Insert Table 12 about here)

The results in Table 12 shows that our results are indeed consistent and slightly statistically weaker results, within each respective sub-sample. For example, we show that, based on value-weighted approach, the purchase transactions by sample investors return 0.044 percent after the traffic accidents, which is 0.1 percentage higher than the alpha of the portfolios following the same investors' purchase decisions before their respective accident (0.034) for the first half of 2015. On the other hand, the alpha of the portfolio of sample investors' sale transactions after accidents is 0.021 percent, which is 0.015 percentage lower than the alpha of the portfolio of sample investors' sale transactions before accidents (0.036).

[8] The results are available upon request.

Taken together, the alpha of a portfolio that long stocks picked by sample investors and short sell stocks stock by sample investors reports an alpha of 0.023 percent after the accidents, 0.025 percentage higher than the alpha of the portfolio following the same strategy before the accidents (-0.001). Consistent with our main findings, the beta of investor portfolio decreases and investors' portfolio tilt towards large instead of small stocks after investors experience traffic accidents, whereas the shift in investors' preference for value versus growth stocks is not statistically significant. The value-weighted results depict the same picture.

For the first half of 2015, we find significant reduction in the market beta, SMB, and HML loadings of investors' portfolios after experiencing traffic accidents than before the accidents, again suggesting reduced risk preference. In addition, we also find significant improvement in sample investors' risk-adjusted returns after traffic accidents. In sum, our sub-sample analyses for the sub-periods of 2015 confirm that our results are not driven by any particular market environment.

We perform further robustness tests by examining the results within each individual province. Our results are qualitatively the same within all provinces with the results being significant in some provinces. Such results are available upon request.

To avoid any spurious effects in sample slicing, we also conduct robustness tests on alternative insurance policy types and observations (IDs). As mentioned in the data section, we merge the automobile insurance datasets with stock market transactions records according to Chinese citizen ID in insurance filings and brokerage accounts. There are different policy types and IDs in our insurance datasets, which may lead to distinct empirical results. To confirm the robustness of our empirical results, we re-build the transaction-based calendar time portfolios based on third-party insurance policy using ID of drivers as our bridge to merge data. The results are shown in Table

13 and Table 14, respectively.

(Insert Table 13 and 14 about here)

As shown in the Table 13 and 14, our conclusions still hold for alternative policy types and observations. The consistency lies in both tests for abnormal returns and beta coefficients – investors obtain relatively higher abnormal returns and take lower Market and SMB betas after experiencing automobile accidents.[9]

5. Conclusions

The current study investigates the interaction between real life experience and risk taking in financial decisions and provide novel evidence on how risk preference may be influenced by exogenous and transitory shocks outside the decision making context.

Our findings stress the importance of the complexity of decision making and require additional studies to further understand risk preference formulation and investor behavior. Such results are important to understand important phenomenon in finance such as stock market participation, asset allocation, and equity risk premium, and also motivate future studies of utility function and risk preference.

[9] We also experiment with sub-samples of investors within different age groups, income groups, geographical areas and our results remain consistent within most respective sub-samples.

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Table 1. Descriptive Statistics of Insurance Sample

This table shows basic statistics of insurance dataset and macro-economic factors for the whole sample and sub-sample of each area. Insurance records come from Chinese Insurance Information Technology Company (CIITC), a state-owned agency that compiles and manages complete China's insurance market information data. Macro statistics come from Yearbook of China's Insurance (2016) and China Statistical Yearbook (2016). Panel A presents the number of valid IDs for each insurance policies and provides descriptive statistics for age and gender. Panel B presents the area breakdown for automobile accidents in sample. Panel C presents the area breakdown for statistics of macro-economic factors and insurance industry.

Panel A: Description of Automobile Accidents

	Collision Policy	Third Party Policy	Death or Wound Involved
# of Accident	16,425,210	5,810,630	3,015,601
# of Valid ID (Insurer)	13,817,865	4,505,478	1,732,038
# of Valid ID (Insured)	14,419,494	4,713,059	1,848,260
# of Valid ID (Driver)	897,357	204,271	40,551
# of Valid ID (Wounded)	--	--	1,351,984
Insured Description			
Age	38.05	39.41	38.50
Gender (Male=1;Female=0)	72.21%	80.01%	34.65%

Panel B: Area Breakdown of Car Accidents

Area	# of Accident (Collision Policy)	# of Accident (Third Party Policy)	# of Accident (Death or Wound Involved)
Guangdong	2,810,436	781,943	316,844
Jiangsu	2,023,514	562,999	250,307
Shandong	1,634,278	539,626	284,213
Zhejiang	1,687,453	824,156	452,451
Henan	545,286	187,919	164,329
Sichuan	1,459,957	301,222	171,061
Hebei	719,846	280,690	192,525
Hubei	531,721	230,003	110,826
Hunan	423,371	235,311	167,542
Liaoning	555,662	313,678	104,032
Total (Sample)	12,391,524	4,257,547	2,214,130
Total (Nationwide)	16,425,210	5,810,630	3,015,601
Total (Sample) / Total (Nationwide)(%)	75.44%	73.27%	73.42%

Panel C: Area Breakdown of Macro Factors

Area	GDP (in billion RMB)	Population (in million)	Automobile Ownership (in million)	Premium Income (All Insurance) (in billion RMB)	Premium Income (Property Insurance) (in billion RMB)
Guangdong	7,281.26	108.49	27.64	217.05	66.91
Jiangsu	7,011.64	79.76	23.11	198.99	67.22
Shandong	6,300.23	98.47	28.63	154.24	47.33
Zhejiang	4,288.60	55.39	20.98	120.71	52.55
Henan	3,701.03	94.80	17.89	124.88	32.02
Sichuan	3,010.31	82.04	14.43	126.62	42.10
Hebei	2,980.61	74.25	20.54	116.31	39.95
Hubei	2,955.02	58.52	9.27	84.38	23.85
Hunan	2,904.72	67.83	9.66	71.22	24.32
Liaoning	2,870.00	43.82	10.61	70.51	20.97
Total (Sample)	43,303.41	763.37	182.75	1,284.89	417.21
Total (Nationwide)	72,349.95	1,374.62	303.84	2,269.16	735.51
Total (Sample) / Total (Nationwide)(%)	59.85%	55.53%	60.15%	56.62%	56.72%

Table 2: Description of Stock Market Investment Data

This table shows the descriptive statistics for stock market investment dataset. Stock market investment records come from a large national brokerage firm in China. Panel A presents the summary statistics for investors' holding and trading characteristics. Turnover is calculated as sum of transaction value divided by average of position value at the beginning and end of the day. Holding period is in trading day terms. Panel B presents summary statistics for investors' personal characteristics. Income and educational background are self-reported when registering the brokerage accounts. Age is calculated as difference between Jan 1, 2015 between birthday in yearly terms. Investment experience is calculated as difference between Jan 1, 2015 between brokerage account registering date in yearly terms.

Panel A: Portfolio and Trading Characteristics

	Average	Std.	25%	Median	75%
Number of Trades (Ann.)	96.06	44.44	122.42	92.58	35.96
Daily Turnover (%)	4.81	4.63	6.12	4.69	0.84
Number of Stocks in Portfolios	2.41	1.56	5.49	3.74	0.90
Portfolio Value (RMB)	280,368.25	157,738.79	489,223.09	380,108.04	161,040.00
Holding Period (Days)	19.74	53.74	1.00	4.00	12.00

Panel B: Investor Characteristics

	Average	Std.	25%	Median	75%
Self-Reported Income (Ann.)	585,088.94	337,259.67	944,225.35	503,977.03	347,688.15
Investment Experience (Years)	2.87	5.41	7.31	5.07	1.09
Age	38.25	8.89	42.14	38.57	34.90
Gender (Male=1;Female=0)	0.53				
Breakdown of Educational Background (%)					
High School and Below	37.19%				
Undergraduate	43.83%				
Graduate	18.98%				
Number of Obs.	2,388,187				

Table 3: Description of Merged Sample

This table shows the descriptive statistics for merged sample of insurance and stock market investment datasets. Insurance policy filings and stock market investment records are merged according to unique ID of each Chinese citizen. Panel A presents the number of merged observations in each insurance policy. Panel B presents the summary statistics for investors' holding and trading characteristics. Turnover is calculated as sum of transaction value divided by average of position value at the beginning and end of the day. Holding period is in trading day terms. Panel C presents summary statistics for investors' personal characteristics. Income and educational background are self-reported when registering the brokerage accounts. Age is calculated as difference between Jan 1, 2015 between birthday in yearly terms. Investment experience is calculated as difference between Jan 1, 2015 between brokerage account registering date in yearly terms.

Panel A: Number of Observations in each Sub-sample

	Collision Policy	Third Party Policy	Death or Wound Involved
# of Matched ID (Insurer)	58,505	20,238	5,638
% of Matched ID (Insurer)	0.423%	0.449%	0.326%
# of Matched ID (Insured)	60,481	20,854	5,842
% of Matched ID (Insured)	0.419%	0.442%	0.316%
# of Matched ID (Driver)	4,227	1,320	232
% of Matched ID (Driver)	0.471%	0.646%	0.572%
# of Matched ID (Wounded)	--	--	1,201
% of Matched ID (Wounded)	--	--	0.089%

Panel B: Portfolio and Trading Characteristics

	Average	Std.	25%	Median	75%
Number of Trades (Ann.)	244.21	112.97	311.24	221.10	67.01
Number of Unique Stocks in All Transactions	37.44	36.04	47.72	36.54	6.53
Daily Turnover (%)	21.75	14.07	49.47	33.68	8.14
Number of Stocks in Portfolio	2.65	1.49	4.63	3.60	1.52
Portfolio Size (RMB)	288,556.24	67,061.89	317,928.18	290,968.06	263,310.45
Daily Portfolio Returns	0.08%	0.07%	0.10%	0.07%	0.01%
Holding Period (Days)	16.89	47.37	1.00	4.00	11.00

Panel C: Investor Characteristics

	Average	Std.	25%	Median	75%
Self-Reported Income (Ann.)	623,253.13	353,647.31	984,419.56	524,748.20	332,862.30
Investment Experience (Years)	2.37	4.62	6.48	4.31	0.89
Age	37.05	7.29	44.56	38.18	34.24
Gender (Male=1;Female=0)	0.58				
Breakdown of Educational Background (%)					
High School and Below	23.75%				
Undergraduate	47.85%				
Graduate	28.40%				
Number of Obs.	64,214				

Table 4: Change in Trading Activities Around Automobile Accidents

This table shows the changes in investors' transaction characteristics before and after automobile accidents. The results are based on **collision insurance claims** and the corresponding IDs of **the insured**. Time windows are calendar days relative to insurance claim dates. Turnover is calculated as sum of transaction value divided by average of position value at the beginning and end of the day. T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Time Window	(-30,-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
Var	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
# of Stocks in Portfolio	3.01	3.96	0.95***	3.24	4.02	0.77***	3.37	3.96	0.60***
			(100.71)			(97.28)			(90.61)
Turnover (%)	32.28	17.72	-14.56***	23.63	17.27	-6.36***	16.57	15.72	-0.84***
			(-6.41)			(-11.37)			(-11.63)
Turnover for Buying (%)	17.31	9.81	-7.50***	12.95	9.70	-3.25***	9.22	8.67	-0.55***
			(-117.47)			(-90.93)			(-59.43)
Turnover for Selling (%)	14.97	7.91	-7.06***	10.68	7.57	-3.11***	7.35	7.05	-0.30***
			(-90.61)			(-68.02)			(-30.67)
Daily Transaction #	1.35	1.03	-0.31***	1.08	0.98	-0.11***	0.79	0.85	0.07***
			(-19.26)			(-3.83)			(7.40)
Daily Transaction # for Buying	0.76	0.59	-0.17***	0.62	0.56	-0.06***	0.45	0.48	0.03***
			(-17.25)			(-6.09)			(4.03)
Daily Transaction # for Selling	0.59	0.45	-0.14***	0.47	0.42	-0.05	0.33	0.37	0.04***
			(-16.22)			(-0.60)			(12.25)
Value each Transaction	74,689	55,555	-19,134***	58,625	50,801	-7,825***	42,934	40,095	-2,839***
			(-7.85)			(-3.95)			(-4.55)
Value each Buying	37,215	27,661	-9,553***	29,891	25,842	-4,049***	21,815	20,638	-1,177***
			(-7.95)			(-4.33)			(-3.93)
Value each Selling	37,475	27,894	-9,581***	28,734	24,959	-3,776***	21,119	19,456	-1,663***
			(-6.11)			(-3.79)			(-4.35)
Number of Obs.		29,885			34,034			40,596	

Table 5. Changes in Portfolio Characteristics around Automobile Accidents

This table shows the changes in investors' portfolio characteristics before and after automobile accidents. The results are based on **collision insurance claims** and the corresponding IDs of **the insured**. Time windows are calendar days relative to insurance claim dates. Holding percentage is calculated as position value of corresponding stocks (Small and Medium Enterprise, ChiNext, and Special Treatment) divided by portfolio value at the end of the day. log(Mktcap) and log(BM) are adjusted by median of all stocks in China A shares. Idiosyncratic volatility (Ivol) is calculated by running daily portfolio returns on daily Fama-French 3 factors. T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Time Window	(-30,-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
Var	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Small and Medium Enterprise Holdings (%)	16.83	16.81	-0.02***	16.94	16.87	-0.07***	17.89	17.29	-0.59***
			(-3.11)			(-3.59)			(-3.20)
ChiNext Holdings (%)	5.15	5.07	-0.08***	5.13	4.98	-0.15***	5.39	4.86	-0.54***
			(-4.26)			(-8.90)			(-20.04)
Special Treatment Holdings (%)	0.82	0.78	-0.03***	0.81	0.78	-0.03***	0.90	0.79	-0.11***
			(-2.71)			(-4.13)			(-4.42)
log(Mktcap)	7.27	7.33	0.06***	7.24	7.34	0.10***	7.16	7.31	0.15***
			(26.15)			(45.8)			(69.96)
log(BM)	-0.381	-0.379	0.002***	-0.385	-0.378	0.006***	-0.390	-0.387	0.004***
			(5.32)			(4.35)			(5.09)
Ivol (%)	2.08	2.01	-0.07***	2.33	2.13	-0.20***	2.72	2.16	-0.56***
			(-10.57)			(-29.71)			(-44.16)
Number of Obs.	29,885			34,034			40,596		

Table 6: Investment Performance Around Accidents
(Transaction Based Calendar Time Portfolios)

This table shows the abnormal returns and betas of transaction-based calendar time portfolios. The results are based on **collision insurance claims** and the corresponding IDs of **the insured**. Time windows are calendar days relative to insurance claim dates. Only transactions within time windows are included in analysis. Portfolios are formed by mimicking the trades of all investors in our sample. Stocks are held in a calendar-time portfolio for 30 calendar days. For a given group of stocks, we form one calendar-time portfolio based on stocks bought ("Buy") and another portfolio based on stocks sold ("Sell"). We show the difference of returns between the Buy and Sell portfolios ("Total"). The beta coefficients and alpha report the coefficients and constant from a regression of the Buy, Sell, and Total portfolio returns on daily Fama-French 3 factors. Panel A presents the results of equally-weighted portfolios and Panel B presents the results of dollar-weighted portfolios (weighted by transaction value). T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Equal Weight

Time Window	(-30,-10,10,30)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.139***	1.127***	-0.012	1.142***	1.220***	0.077*	-0.004	-0.092	-0.089***
	(55.25)	(49.95)	(-1.10)	(53.03)	(56.29)	(1.90)	(-1.08)	(-1.31)	(-2.69)
SMB	0.517***	0.421***	-0.095***	0.543***	0.474***	-0.069**	-0.026***	-0.053	-0.027**
	(8.91)	(8.14)	(-3.12)	(8.96)	(8.47)	(-2.07)	(-2.88)	(-1.24)	(-2.09)
HML	-0.022	0.013	0.035**	-0.022	-0.090	-0.068**	0.000	0.104**	0.103***
	(-0.38)	(0.21)	(2.21)	(-0.36)	(-1.63)	(-2.07)	(0.01)	(2.04)	(3.21)
Alpha (%)	-0.074***	-0.057**	0.018***	-0.041	-0.044	-0.003	-0.033***	-0.013***	0.021***
	(-2.72)	(-2.21)	(3.43)	(-1.44)	(-0.42)	(-0.92)	(-8.47)	(-3.30)	(3.35)
Alpha (Ann.)	-18.87%	-14.41%	4.46%	-10.46%	-11.22%	-0.76%	-8.42%	-3.19%	5.23%
Number of Obs.		244			244			244	

Time Window	(-60,-15,15,60)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.139***	1.092***	-0.047***	1.090***	1.123***	0.033	0.049	-0.031	-0.080***
	(40.09)	(42.57)	(-3.34)	(39.75)	(57.83)	(1.05)	(0.55)	(-0.96)	(-3.96)
SMB	0.388***	0.351***	-0.037**	0.410***	0.532***	0.122	-0.022**	-0.181	-0.159***
	(5.04)	(6.96)	(-2.40)	(5.29)	(9.70)	(1.40)	(-2.32)	(-0.13)	(-4.38)
HML	0.013	-0.011	-0.024	0.012	-0.023	-0.035	0.001	0.012	0.011
	(0.17)	(-0.14)	(-0.24)	(0.16)	(-0.41)	(-0.40)	(0.07)	(0.25)	(0.27)
Alpha (%)	-0.066***	-0.050***	0.016***	-0.056	-0.059	-0.003	-0.010	0.009*	0.018**
	(-2.82)	(-3.77)	(3.07)	(-1.00)	(-1.14)	(-0.17)	(-1.30)	(-1.66)	(2.20)
Alpha (Ann.)	-16.83%	-12.85%	3.98%	-14.32%	-15.05%	-0.73%	-2.51%	2.19%	4.70%
Number of Obs.	240			240			240		

Time Window	(-180,-15,15,180)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.137***	1.091***	-0.046**	1.089***	1.122***	0.033	0.048	-0.031	-0.078***
	(40.09)	(42.43)	(-2.31)	(39.82)	(57.66)	(1.06)	(0.55)	(-0.89)	(-3.89)
SMB	0.532***	0.388***	-0.144***	0.409***	0.534***	0.125***	0.122**	-0.146	-0.269***
	(5.04)	(7.02)	(-4.46)	(5.30)	(9.72)	(3.43)	(2.10)	(-0.06)	(-5.46)
HML	0.012	-0.013	-0.025	0.011	-0.026	-0.036	0.001	0.013	0.011
	(0.16)	(-0.17)	(-0.25)	(0.14)	(-0.46)	(-0.41)	(0.13)	(0.27)	(0.28)
Alpha (%)	-0.064*	-0.051***	0.013***	-0.056**	-0.075**	-0.019***	-0.008	0.024*	0.032***
	(-1.77)	(-2.79)	(4.00)	(-2.03)	(-2.08)	(-3.23)	(-1.17)	(1.76)	(3.49)
Alpha (Ann.)	-16.32%	-13.06%	3.26%	-14.28%	-19.13%	-4.85%	-2.04%	6.07%	8.11%
Number of Obs.	240			240			240		

Panel B: Dollar Weight

Time Window	(-30-10,10,30)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.138***	1.113***	-0.025	1.134***	1.212***	0.077***	0.003	-0.099	-0.102***
	(55.44)	(47.09)	(-1.28)	(52.05)	(36.49)	(2.79)	(0.69)	(-0.06)	(-3.11)
SMB	0.482***	0.431***	-0.051***	0.433***	0.497***	0.064	0.048	-0.066	-0.115***
	(7.48)	(7.23)	(-2.89)	(7.07)	(4.63)	(0.45)	(0.14)	(-1.62)	(-4.59)
HML	-0.106*	-0.091	0.014	-0.116*	-0.163*	-0.047	0.010	0.072	0.061**
	(-1.85)	(-1.39)	(0.27)	(-1.91)	(-1.92)	(-0.58)	(0.76)	(1.41)	(2.15)
Alpha (%)	-0.056**	-0.038*	0.018**	-0.053	-0.048	0.005	-0.003***	0.010**	0.013**
	(-2.06)	(-1.81)	(2.02)	(-0.92)	(-0.03)	(0.72)	(-5.07)	(2.52)	(2.12)
Alpha (Ann.)	-14.28%	-9.61%	4.68%	-13.52%	-12.24%	1.28%	-0.77%	2.64%	3.40%
Number of Obs.		244			244			244	

Time Window	(-60,-15,15,60)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.073***	1.130***	0.057***	1.070***	1.129***	0.059	0.003	0.001	-0.002
	(44.52)	(39.59)	(-2.61)	(41.26)	(34.85)	(1.46)	(0.40)	(0.11)	(-0.19)
SMB	0.211***	0.478***	0.267***	0.208***	0.481***	0.273**	0.003	-0.003	-0.006
	(3.10)	(5.93)	(-2.68)	(2.84)	(5.25)	(2.38)	(0.13)	(-0.12)	(-0.16)
HML	-0.088	-0.096	-0.008	-0.117	-0.071	0.046	0.028	-0.025	-0.053
	(-1.29)	(-1.18)	(-0.07)	(-1.58)	(-0.77)	(0.39)	(1.19)	(-1.04)	(-1.43)
Alpha (%)	-0.074	-0.077	-0.003	-0.017	-0.038	-0.021	-0.057***	-0.039**	0.018**
	(-1.15)	(-1.12)	(-0.12)	(-0.25)	(-0.44)	(-0.19)	(-2.83)	(-2.44)	(2.27)
Alpha (Ann.)	-18.87%	-19.70%	-0.83%	-4.34%	-9.69%	-5.36%	-14.54%	-10.01%	4.52%
Number of Obs.		240			240			240	

Time Window	(-180,-15,15,180)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.126***	1.070***	-0.057***	1.067***	1.129***	0.062	0.059	-0.060	-0.119***
	(44.70)	(38.94)	(-2.58)	(41.45)	(34.63)	(1.54)	(0.31)	(-0.37)	(-3.45)
SMB	0.483***	0.213***	-0.270***	0.211***	0.479***	0.268**	0.272	-0.266	-0.538***
	(3.15)	(5.91)	(-2.67)	(2.90)	(5.20)	(2.35)	(0.09)	(-0.16)	(-5.05)
HML	-0.091	-0.083	0.008	-0.118	-0.069	0.050	0.027	-0.014	-0.042
	(-1.34)	(-1.01)	(0.08)	(-1.61)	(-0.74)	(0.43)	(1.18)	(-0.61)	(-1.18)
Alpha (%)	-0.075	-0.080	-0.005	-0.016	-0.032	-0.016	-0.059***	-0.048**	0.011**
	(-1.18)	(-1.04)	(-0.05)	(-0.24)	(-0.36)	(-0.14)	(-3.05)	(-2.50)	(2.31)
Alpha (Ann.)	-19.13%	-20.40%	-1.28%	-4.08%	-8.16%	-4.08%	-15.05%	-12.24%	2.81%
Number of Obs.	240			240			240		

Table 7: Investment Performance Around Accidents
(Holding Based Calendar Time Portfolios)

This table shows the abnormal returns and betas of holding-based calendar time portfolios. The results are based on **collision insurance claims** and the corresponding IDs of **the insured**. Time windows are calendar days relative to insurance claim dates. Only holding returns within time windows are included in analysis. The beta coefficients and alpha report the coefficients and constant from a regression of investors' portfolio returns on daily Fama-French 3 factors. Panel A presents the results of equally-weighted portfolios and Panel B presents the results of dollar-weighted portfolios (weighted by position value). T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Equal Weight

Time Window	(-30-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	0.927***	0.922***	-0.005	0.915***	0.916***	0.001	0.925***	0.914***	-0.011
	(57.80)	(58.97)	(-1.62)	(49.84)	(51.13)	(0.39)	(50.04)	(50.99)	(-0.28)
SMB	0.333***	0.232***	-0.101***	0.273***	0.234***	-0.039**	0.363***	0.292***	-0.071***
	(6.53)	(6.87)	(-3.98)	(4.74)	(5.23)	(-2.46)	(4.76)	(5.20)	(-3.51)
HML	0.064*	0.064*	0.000	0.029	0.043	0.014**	0.029	0.041	0.012**
	(1.75)	(1.80)	(-0.01)	(0.69)	(1.03)	(2.15)	(0.69)	(0.98)	(2.06)
Alpha (%)	-0.053***	-0.039***	0.014***	-0.072***	-0.047***	0.025***	-0.069***	-0.050***	0.019***
	(-2.87)	(-3.26)	(2.73)	(-3.62)	(-3.87)	(3.03)	(-3.64)	(-3.83)	(2.92)
Alpha (Ann.)	-14.54%	-7.84%	6.69%	-22.31%	-16.75%	5.57%	-24.61%	-19.18%	5.43%
Number of Obs.		231			231			231	

Panel B: Dollar Weight

Time Window	(-30-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	0.971***	0.950***	-0.021	0.924***	0.937***	0.013	0.978***	0.938***	-0.039**
	(52.53)	(53.74)	(-1.11)	(45.40)	(56.03)	(0.79)	(49.06)	(54.64)	(-2.27)
SMB	0.371***	0.270***	-0.101***	0.293***	0.277***	-0.016***	0.362***	0.295***	-0.067***
	(6.31)	(6.58)	(-3.02)	(3.03)	(5.29)	(-2.64)	(2.76)	(5.47)	(-2.59)
HML	-0.068	-0.071*	-0.003	-0.106**	-0.119***	-0.012	-0.109**	-0.140***	-0.031
	(-1.62)	(-1.77)	(-0.07)	(-2.25)	(-3.06)	(-0.33)	(-2.52)	(-3.52)	(-0.81)
Alpha (%)	-0.057	-0.031***	0.026	-0.088***	-0.066***	0.022***	-0.097***	-0.075***	0.021
	(-1.36)	(-3.06)	(1.52)	(-3.95)	(-5.41)	(2.62)	(-4.74)	(-5.05)	(-0.11)
Alpha (Ann.)	-13.39%	-9.86%	3.53%	-18.36%	-12.03%	6.33%	-17.49%	-12.67%	4.82%
Number of Obs.	231			231			231		

Table 8: Investment Performance Around Accidents
(Event Time Portfolios)

This table shows the returns of event time portfolios. The results are based on **collision insurance claims** and the corresponding IDs of **the insured**. Event dates (t=0) are set to corresponding insurance claim dates. Time windows are calendar days relative to insurance claim dates. Only transactions within time windows are included in analysis. Portfolios are formed by mimicking the trades of all investors in our sample. T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Time Window	(-30-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
Portfolio Returns (Ann.)	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Equally-Weighted (%)	5.859	8.497	2.639***	4.278	9.457	5.179***	5.090	12.553	7.463***
			(8.41)			(20.00)			(26.47)
Dollar-Weighted (%)	5.249	7.352	2.102***	3.822	8.546	4.723***	4.337	12.502	8.164***
			(6.75)			(17.99)			(26.33)
Number of Obs.	29,885			34,034			40,596		

Table 9: Investment Performance Around Accidents
(Self-Benchmark Abnormal Returns)

This table shows the returns of self-benchmark portfolios. The results are based on **collision insurance claims** and the corresponding IDs of **the insured**. Following Barber and Odean (2000), we form self-benchmark portfolios as the portfolio held by each investor on one day before insurance claim date. It represents the return that the investor would have earned if it had merely held its before-accident portfolio in the entire time window. The "Realized" portfolio returns are the investor's real holding returns. Abnormal return is calculated as "Realized" minus "Benchmark". It will be zero if the investor does not trade any stock. T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Time Window	(-30-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
Portfolio Returns (Ann.)	Benchmark	Realized	Abnormal	Benchmark	Realized	Abnormal	Benchmark	Realized	Abnormal
Equally-Weighted (%)	32.191	42.038	9.847***	26.256	31.723	5.466***	32.966	19.659	13.308***
			(3.90)			(6.74)			(5.16)
Dollar-Weighted (%)	31.184	39.375	8.191***	25.679	29.770	4.092***	25.962	22.699	3.262*
			(9.66)			(5.06)			(1.66)
Number of Obs.		29,885			34,034			40,596	

Table 10: Influence of Body Injury in Accidents on Investment Performance

This table shows the abnormal returns and betas of transaction-based calendar time portfolios for two sub-samples – with bodily injury and without bodily injury. The results are based on **collision insurance claims** and the corresponding IDs of **the drivers**. Time windows are calendar days relative to insurance claim dates. Only transactions within time windows are included in analysis. Portfolios are formed by mimicking the trades of all investors in our sample. Stocks are held in a calendar-time portfolio for 30 calendar days. For each sub-sample, we form two calendar-time portfolios based on investors' transactions before and after the automobile accidents and then calculate the "After Minus Before" portfolio returns. We show the difference of returns ("Diff") between with-bodily-injury and without-bodily-injury sub-samples. The beta coefficients and alpha report the coefficients and constant from a regression of the portfolio returns on daily Fama-French 3 factors. Panel A presents the results of equally-weighted portfolios and Panel B presents the results of dollar-weighted portfolios (weighted by transaction value). T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Equal Weight

Time Window	(-30-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
	After-Before	After-Before	Diff	After-Before	After-Before	Diff	After-Before	After-Before	Diff
Body Injury ?	No	Yes	Yes-No	No	Yes	Yes-No	No	Yes	Yes-No
Mkt	0.022*	0.119***	0.096**	0.019	0.015	-0.004	0.017	0.019	0.002
	(1.73)	(2.90)	(2.29)	(1.17)	(0.81)	(-0.20)	(1.08)	(1.09)	(0.18)
SMB	0.070*	-0.090	-0.160**	0.013	-0.074	-0.087	0.016	-0.020	-0.036
	(1.93)	(-1.17)	(-2.54)	(0.30)	(-1.46)	(-1.33)	(0.36)	(-0.40)	(-1.45)
HML	0.074**	0.158	0.084	0.017	-0.045	-0.063*	0.017	-0.029	-0.047
	(2.06)	(1.39)	(1.41)	(0.39)	(-0.90)	(-1.91)	(0.39)	(-0.58)	(-1.26)
Alpha (%)	0.009	0.032***	0.023**	-0.015	0.046***	0.060***	-0.013	0.036***	0.049**
	(1.30)	(3.32)	(2.44)	(-0.30)	(3.47)	(2.77)	(-0.58)	(3.03)	(2.05)
Alpha (Ann.)	2.30%	8.10%	5.80%	-3.70%	11.60%	15.30%	-3.21%	9.18%	12.39%
Number of Obs.		244			240			240	

Panel B: Dollar Weight

Time Window	(-30-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
	After-Before	After-Before	Diff	After-Before	After-Before	Diff	After-Before	After-Before	Diff
Body Injury ?	No	Yes	Yes-No	No	Yes	Yes-No	No	Yes	Yes-No
Mkt	-0.002	0.116**	0.118**	-0.002	0.029	0.031	-0.004	0.021	0.026
	(-0.10)	(2.24)	(2.36)	(-0.15)	(1.17)	(1.17)	(-0.35)	(0.97)	(1.41)
SMB	0.079	-0.158***	-0.237***	-0.013	-0.117***	-0.105**	-0.005	-0.151***	-0.146***
	(1.45)	(-2.89)	(-3.92)	(-0.35)	(-3.67)	(-2.37)	(-0.15)	(-3.44)	(-3.38)
HML	0.054	0.151***	0.097	-0.055	0.029	0.084***	-0.045	0.001	0.046
	(1.01)	(3.05)	(1.38)	(-1.47)	(0.41)	(3.23)	(-1.27)	(0.02)	(1.08)
Alpha (%)	-0.023	0.021***	0.044**	0.007	0.045***	0.038**	0.008	0.058***	0.050***
	(-1.14)	(2.69)	(2.44)	(0.20)	(4.20)	(2.21)	(0.24)	(3.96)	(2.61)
Alpha (Ann.)	-5.93%	5.27%	11.20%	1.79%	11.35%	9.56%	2.04%	14.88%	12.84%
Number of Obs.		244			240			240	

Table 11: Influence of Accident Damage on Investment Performance

This table shows the abnormal returns and betas of transaction-based calendar time portfolios for two sub-samples – high damage (above the median) and low damage (above the median). The results are based on **collision insurance claims** and the corresponding IDs of **the insured**. Time windows are calendar days relative to insurance claim dates. Only transactions within time windows are included in analysis. Portfolios are formed by mimicking the trades of all investors in our sample. Stocks are held in a calendar-time portfolio for 30 calendar days. For each sub-sample, we form two calendar-time portfolios based on investors' transactions before and after the automobile accidents and then calculate the "After Minus Before" portfolio returns. We show the difference of returns ("Diff") between high-damage and low-damage sub-samples. The beta coefficients and alpha report the coefficients and constant from a regression of the portfolio returns on daily Fama-French 3 factors. Panel A presents the results of equally-weighted portfolios and Panel B presents the results of dollar-weighted portfolios (weighted by transaction value). T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Equal Weight

Time Window	(-30-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
	After-Before	After-Before	Diff	After-Before	After-Before	Diff	After-Before	After-Before	Diff
Damage	Low	High	High-Low	Low	High	High-Low	Low	High	High-Low
Mkt	0.023	0.020	-0.003	0.053*	-0.068*	-0.121***	0.050*	0.107***	0.056*
	(1.40)	(1.06)	(-0.15)	(1.94)	(-1.91)	(-2.99)	(1.86)	(4.67)	(1.81)
SMB	0.104**	-0.095***	-0.199***	0.057	-0.212***	-0.269***	0.059	-0.215***	-0.274***
	(2.23)	(-3.68)	(-4.40)	(0.74)	(-3.24)	(-2.72)	(0.77)	(-4.93)	(-3.73)
HML	0.076*	0.138***	0.062	0.091	-0.005	-0.095	0.090	-0.005	-0.095
	(1.65)	(2.64)	(0.98)	(1.18)	(-0.17)	(-1.31)	(1.18)	(-0.16)	(-1.45)
Alpha (%)	-0.008	0.040***	0.048***	0.009	0.041***	0.032*	0.001	0.038***	0.037***
	(-0.81)	(3.99)	(4.38)	(0.45)	(4.78)	(1.81)	(0.62)	(2.95)	(3.23)
Alpha (Ann.)	-2.17%	10.10%	12.27%	2.30%	10.48%	8.19%	0.26%	9.69%	9.44%
Number of Obs.		244			240			240	

Panel B: Dollar Weight

Time Window	(-30-10,10,30)			(-60,-15,15,60)			(-180,-15,15,180)		
	After-Before	After-Before	Diff	After-Before	After-Before	Diff	After-Before	After-Before	Diff
Damage	Low	High	High-Low	Low	High	High-Low	Low	High	High-Low
Mkt	-0.015	-0.127**	-0.112**	0.041	-0.129***	-0.171***	0.038	-0.095	-0.133
	(-0.52)	(-2.58)	(-2.29)	(1.01)	(-2.87)	(-3.79)	(0.86)	(-0.91)	(-1.23)
SMB	0.073	-0.143***	-0.216***	0.020	-0.059**	-0.079	0.016	-0.055*	-0.070
	(0.91)	(-3.10)	(-2.58)	(0.18)	(-1.97)	(-0.73)	(0.13)	(-1.90)	(-0.75)
HML	0.060	0.082***	0.023	0.053	-0.158	-0.211*	0.055	-0.143**	-0.198
	(0.76)	(2.64)	(0.31)	(0.45)	(-1.52)	(-1.66)	(0.44)	(-2.48)	(-1.60)
Alpha (%)	0.008	0.046***	0.038***	-0.006	0.053***	0.059***	-0.012	0.047***	0.059***
	(0.01)	(4.43)	(4.97)	(-0.03)	(4.21)	(3.98)	(0.00)	(4.22)	(4.05)
Alpha (Ann.)	2.04%	11.70%	9.66%	-1.53%	13.39%	14.92%	-3.06%	12.02%	15.08%
Number of Obs.		244			240			240	

Table 12: Robustness Tests – Sub Samples in Different Time Periods

This table shows the abnormal returns and betas of transaction-based calendar time portfolios in different time periods for robustness check. The results are based on **collision insurance claims** and the corresponding IDs of **the insured**. Time windows are calendar days relative to insurance claim dates. Only transactions within time windows are included in analysis. Portfolios are formed by mimicking the trades of all investors in our sample. Stocks are held in a calendar-time portfolio for 30 calendar days. For a given group of stocks, we form one calendar-time portfolio based on stocks bought ("Buy") and another portfolio based on stocks sold ("Sell"). We show the difference of returns between the Buy and Sell portfolios ("Total"). The beta coefficients and alpha report the coefficients and constant from a regression of the Buy, Sell, and Total portfolio returns on daily Fama-French 3 factors. Panel A presents the results of equally-weighted portfolios and Panel B presents the results of dollar-weighted portfolios (weighted by transaction value). T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Equal Weight

Sub Sample	1-2 Q		Time Window	(-30-10,10,30)					
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.078***	1.021***	-0.057*	1.015***	1.057***	0.041*	0.063	-0.036	-0.099***
	(35.15)	(36.51)	(-1.90)	(35.22)	(56.47)	(1.72)	(0.79)	(-1.02)	(-2.98)
SMB	0.346	0.106***	-0.239***	0.138	0.391***	0.253***	0.208	-0.284	-0.492***
	(1.12)	(3.57)	(-3.41)	(1.46)	(6.38)	(3.21)	(1.34)	(-0.65)	(-6.26)
HML	-0.058	-0.043	0.015	-0.072	-0.040	0.031	0.014	-0.003	-0.017
	(-0.78)	(-0.57)	(0.19)	(-0.97)	(-0.84)	(0.51)	(0.77)	(-0.05)	(-0.40)
Alpha (%)	0.034**	0.044***	0.010	0.036**	0.021**	-0.015**	-0.001	0.023**	0.025***
	(2.48)	(4.21)	(1.64)	(2.01)	(2.45)	(-2.06)	(-0.64)	(2.19)	(3.00)
Alpha (Ann.)	8.67%	11.22%	2.55%	9.05%	5.36%	-3.70%	-0.38%	5.87%	6.25%
Number of Obs.		128			128			128	

Sub Sample	3-4 Q		Time Window	(-30-10,10,30)					
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.193***	1.086***	-0.108***	1.085***	1.063***	-0.023**	0.108	0.023	-0.085**
	(68.68)	(49.32)	(-2.63)	(67.81)	(58.01)	(-2.47)	(1.31)	(1.46)	(-2.16)
SMB	0.426***	0.406***	-0.020	0.406***	0.449***	0.043	0.020	-0.043	-0.063
	(8.32)	(6.31)	(-0.55)	(9.15)	(7.23)	(1.54)	(0.37)	(-0.42)	(-1.60)
HML	-0.027	-0.007	0.019	-0.038	-0.080*	-0.043*	0.011	0.073*	0.062*
	(-0.66)	(-0.13)	(0.63)	(-0.92)	(-1.71)	(-1.82)	(0.71)	(1.83)	(1.88)
Alpha (%)	-0.133***	-0.118***	0.015	-0.050	-0.031	0.019	-0.083***	-0.087***	-0.004
	(-4.02)	(-2.59)	(0.58)	(-1.25)	(-0.56)	(0.33)	(-7.86)	(-4.50)	(-0.81)
Alpha (Ann.)	-34.00%	-30.18%	3.83%	-12.75%	-7.96%	4.79%	-21.25%	-22.22%	-0.97%
Number of Obs.		132			132			132	

Panel B: Dollar Weight

Sub Sample	1-2 Q		Time Window	(-30-10,10,30)					
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.068***	1.025***	-0.043	1.016***	1.069***	0.053	0.052	-0.045	-0.097**
	(35.43)	(32.50)	(-1.37)	(37.27)	(27.63)	(1.28)	(0.91)	(-0.10)	(-2.56)
SMB	0.297***	0.053	-0.244**	0.058	0.325**	0.267*	0.239**	-0.272***	-0.512***
	(2.76)	(0.56)	(-2.34)	(0.65)	(2.57)	(1.96)	(2.16)	(-2.78)	(-5.39)
HML	-0.134*	-0.137	-0.002	-0.153**	-0.104	0.049	0.019	-0.032	-0.051
	(-1.81)	(-1.62)	(-0.03)	(-2.19)	(-1.05)	(0.46)	(0.76)	(-1.15)	(-1.12)
Alpha (%)	0.018	0.057***	0.039***	0.029***	0.038**	0.010***	-0.011	0.019**	0.030***
	(1.01)	(3.24)	(4.16)	(2.71)	(2.40)	(2.75)	(-1.08)	(2.37)	(3.33)
Alpha (Ann.)	4.53%	14.54%	10.01%	7.27%	9.69%	2.42%	-2.74%	4.85%	7.59%
Number of Obs.		128			128			128	

Sub Sample	3-4 Q		Time Window	(-30-10,10,30)					
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.104***	1.020***	-0.083***	1.050***	1.099***	0.049	0.053	-0.079	-0.132**
	(75.93)	(43.47)	(-2.83)	(68.25)	(31.68)	(1.59)	(0.55)	(0.00)	(-2.19)
SMB	0.416***	0.390***	-0.026	0.332***	0.403***	0.070	0.083	-0.013	-0.096***
	(9.33)	(5.27)	(-0.44)	(8.16)	(3.27)	(0.75)	(0.50)	(-0.87)	(-2.62)
HML	-0.077**	-0.089	-0.012	-0.103**	-0.156*	-0.053	0.026	0.067	0.041
	(-2.05)	(-1.43)	(-0.25)	(-2.49)	(-1.83)	(-0.68)	(1.22)	(1.21)	(0.68)
Alpha (%)	-0.147***	-0.085	0.062**	-0.096**	-0.052	0.044***	-0.051***	-0.033***	0.018**
	(-4.05)	(-1.41)	(2.32)	(-2.40)	(-1.63)	(2.94)	(-2.75)	(-2.67)	(2.47)
Alpha (Ann.)	-37.49%	-21.68%	15.81%	-24.48%	-13.26%	11.22%	-13.01%	-8.42%	4.59%
Number of Obs.		132			132			132	

Table 13: Robustness Tests – Alternative Policy Type

This table shows the abnormal returns and betas of transaction-based calendar time portfolios for robustness check. The results are based on **third-party insurance claims** and the corresponding IDs of **the insured**. Time windows are calendar days relative to insurance claim dates. Only transactions within time windows are included in analysis. Portfolios are formed by mimicking the trades of all investors in our sample. Stocks are held in a calendar-time portfolio for 30 calendar days. For a given group of stocks, we form one calendar-time portfolio based on stocks bought ("Buy") and another portfolio based on stocks sold ("Sell"). We show the difference of returns between the Buy and Sell portfolios ("Total"). The beta coefficients and alpha report the coefficients and constant from a regression of the Buy, Sell, and Total portfolio returns on daily Fama-French 3 factors. Panel A presents the results of equally-weighted portfolios and Panel B presents the results of dollar-weighted portfolios (weighted by transaction value). T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Equal Weight

Time Window	(-30-10,10,30)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.144***	1.144***	0.000	1.124***	1.146***	0.022*	0.020	-0.002	-0.022
	(53.78)	(43.87)	(0.03)	(53.34)	(53.85)	(1.78)	(0.60)	(-0.09)	(-1.30)
SMB	0.520***	0.535***	0.015	0.515***	0.560***	0.045	0.005	-0.025	-0.030
	(8.69)	(7.29)	(0.31)	(9.27)	(8.78)	(1.29)	(0.95)	(-0.38)	(-1.24)
HML	-0.018	-0.012	0.006	-0.077	-0.025	0.052	0.059	0.013	-0.046
	(-0.31)	(-0.17)	(0.12)	(-0.42)	(-1.33)	(1.51)	(0.68)	(1.25)	(-1.20)
Alpha (%)	-0.073***	-0.052*	0.020**	-0.029	-0.026	0.003	-0.043**	-0.026	0.017**
	(-2.58)	(-1.90)	(2.29)	(-1.55)	(-0.47)	(0.90)	(-2.56)	(-0.26)	(2.06)
Alpha (Ann.)	-18.49%	-13.36%	5.13%	-7.48%	-6.63%	0.85%	-11.01%	-6.73%	4.28%
Number of Obs.		244			244			244	

Time Window	(-60,-15,15,60)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.098***	1.139***	0.041	1.095***	1.124***	0.029	0.003	0.015	0.013
	(39.50)	(33.46)	(1.03)	(39.98)	(54.92)	(0.90)	(0.69)	(0.56)	(0.51)
SMB	0.534***	0.408***	-0.127***	0.414***	0.538***	0.125**	0.121	-0.131	-0.251***
	(5.19)	(5.56)	(-3.12)	(5.35)	(9.31)	(2.38)	(0.58)	(-0.05)	(-4.03)
HML	0.009	-0.026	-0.035	-0.002	-0.045	-0.043	0.011	0.019	0.008
	(0.12)	(-0.27)	(-0.31)	(-0.02)	(-0.77)	(-0.47)	(1.03)	(0.25)	(0.11)
Alpha (%)	-0.067*	-0.050	0.017	-0.039	-0.021	0.018	-0.029***	-0.030	-0.001
	(-1.81)	(-1.10)	(1.32)	(-1.05)	(-0.74)	(1.43)	(-6.32)	(-0.90)	(-0.02)
Alpha (Ann.)	-17.09%	-12.75%	4.34%	-9.82%	-5.23%	4.59%	-7.27%	-7.52%	-0.25%
Number of Obs.	240			240			240		

Time Window	(-180,-15,15,180)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.141***	1.098***	-0.043	1.094***	1.226***	0.132***	0.047	-0.128	-0.174***
	(39.52)	(33.30)	(-1.07)	(40.11)	(54.33)	(2.98)	(0.96)	(-0.55)	(-4.46)
SMB	0.535***	0.408***	-0.128***	0.413***	0.534***	0.121**	0.123	-0.126	-0.248***
	(5.20)	(5.53)	(-3.13)	(5.36)	(9.12)	(2.33)	(0.50)	(-0.02)	(-5.10)
HML	0.008	-0.024	-0.032	-0.005	-0.047	-0.042	0.013	0.023	0.009
	(0.10)	(-0.25)	(-0.28)	(-0.07)	(-0.80)	(-0.46)	(1.27)	(0.29)	(0.13)
Alpha (%)	-0.065*	-0.052	0.013**	-0.040	-0.039	0.001	-0.025***	-0.013	0.012**
	(-1.74)	(-1.13)	(2.25)	(-1.10)	(-0.70)	(0.48)	(-5.70)	(-0.97)	(2.22)
Alpha (Ann.)	-16.45%	-13.13%	3.32%	-10.20%	-9.95%	0.26%	-6.25%	-3.19%	3.06%
Number of Obs.	240			240			240		

Panel B: Dollar Weight

Time Window	(-30-10,10,30)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.149***	1.142***	-0.007	1.132***	1.106***	-0.026	0.017*	0.037*	0.019
	(48.75)	(47.02)	(-0.37)	(45.03)	(45.14)	(-1.08)	(1.75)	(1.87)	(0.85)
SMB	0.499***	0.401***	-0.098	0.380***	0.569***	0.189***	0.119**	-0.168**	-0.287***
	(7.52)	(6.01)	(-1.63)	(8.04)	(5.51)	(2.76)	(2.52)	(-2.57)	(-3.58)
HML	-0.095	-0.060	0.035	-0.059	-0.212***	-0.153**	-0.036	0.151***	0.187***
	(-1.45)	(-0.89)	(0.65)	(-0.84)	(-3.10)	(-2.25)	(-1.30)	(2.79)	(2.95)
Alpha (%)	-0.061*	-0.036	0.025***	-0.039	-0.040	-0.002	-0.023**	0.004	0.026**
	(-1.95)	(-1.24)	(3.83)	(-1.15)	(-1.06)	(-0.13)	(-1.97)	(0.60)	(2.51)
Alpha (Ann.)	-15.56%	-9.27%	6.28%	-9.82%	-10.20%	-0.38%	-5.74%	0.93%	6.66%
Number of Obs.		244			244			244	

Time Window	(-60,-15,15,60)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.102***	1.126***	0.024	1.092***	1.116***	0.024	0.010	0.010	0.000
	(38.36)	(39.16)	(0.68)	(38.29)	(55.24)	(0.71)	(1.33)	(0.43)	(0.01)
SMB	0.395***	0.451***	0.056	0.425***	0.443***	0.017	-0.030	0.009	0.039
	(4.87)	(5.56)	(0.57)	(5.28)	(7.76)	(0.18)	(-1.44)	(0.13)	(0.66)
HML	-0.043	-0.075	-0.032	-0.049	-0.139**	-0.090	0.007	0.064	0.058
	(-0.52)	(-0.91)	(-0.32)	(-0.61)	(-2.41)	(-0.94)	(0.32)	(0.96)	(0.97)
Alpha (%)	-0.068*	-0.048	0.020	-0.065*	-0.053	0.012	-0.003	0.005	0.008
	(-1.76)	(-0.63)	(0.93)	(-1.70)	(-0.99)	(0.85)	(-0.64)	(-0.02)	(0.20)
Alpha (Ann.)	-17.21%	-12.24%	4.97%	-16.45%	-13.52%	2.93%	-0.76%	1.28%	2.04%
Number of Obs.	240			240			240		

Time Window	(-180,-15,15,180)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.099***	1.129***	0.030	1.090***	1.124***	0.034	0.009	0.006	-0.004
	(38.99)	(38.22)	(0.84)	(38.55)	(53.40)	(1.02)	(1.58)	(0.24)	(-0.16)
SMB	0.398***	0.455***	0.057	0.425***	0.438***	0.013	-0.027	0.017	0.044
	(4.99)	(5.45)	(0.56)	(5.32)	(7.37)	(0.14)	(-1.64)	(0.25)	(0.71)
HML	-0.038	-0.071	-0.033	-0.048	-0.139**	-0.092	0.010	0.068	0.058
	(-0.47)	(-0.85)	(-0.32)	(-0.59)	(-2.33)	(-0.97)	(0.58)	(1.02)	(0.93)
Alpha (%)	-0.070*	-0.035	0.035***	-0.044*	-0.031	0.013	-0.026	-0.005	0.022***
	(-1.86)	(-0.88)	(3.73)	(-1.74)	(-1.09)	(0.79)	(-0.98)	(-0.24)	(3.00)
Alpha (Ann.)	-17.85%	-8.93%	8.93%	-11.14%	-7.78%	3.36%	-6.72%	-1.15%	5.57%
Number of Obs.	240			240			240		

Table 14: Robustness Tests – Alternative Observation Type

This table shows the abnormal returns and betas of transaction-based calendar time portfolios for robustness check. The results are based on **collision insurance claims** and the corresponding IDs of **the drivers**. Time windows are calendar days relative to insurance claim dates. Only transactions within time windows are included in analysis. Portfolios are formed by mimicking the trades of all investors in our sample. Stocks are held in a calendar-time portfolio for 30 calendar days. For a given group of stocks, we form one calendar-time portfolio based on stocks bought ("Buy") and another portfolio based on stocks sold ("Sell"). We show the difference of returns between the Buy and Sell portfolios ("Total"). The beta coefficients and alpha report the coefficients and constant from a regression of the Buy, Sell, and Total portfolio returns on daily Fama-French 3 factors. Panel A presents the results of equally-weighted portfolios and Panel B presents the results of dollar-weighted portfolios (weighted by transaction value). T-statistics are in parentheses, and ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Equal Weight

Time Window	(-30-10,10,30)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.129***	1.131***	0.002	1.134***	1.118***	-0.016	-0.005	0.013	0.017
	(51.62)	(36.21)	(0.06)	(49.11)	(39.85)	(-0.66)	(-0.66)	(0.89)	(1.26)
SMB	0.477***	0.559***	0.081	0.448***	0.592***	0.144**	0.029*	-0.033	-0.062
	(9.08)	(5.43)	(1.10)	(9.11)	(5.68)	(2.14)	(-1.65)	(-0.72)	(-1.61)
HML	0.018	-0.046	-0.064	0.015	-0.098	-0.113*	0.003	0.052	0.049
	(0.29)	(-0.53)	(-0.87)	(0.23)	(-1.25)	(-1.70)	(0.14)	(1.31)	(1.28)
Alpha (%)	-0.070**	-0.034	0.036**	-0.043	-0.023	0.020**	-0.028***	-0.011**	0.017
	(-2.42)	(-1.22)	(2.56)	(-1.40)	(-1.31)	(1.98)	(-3.22)	(-2.25)	(1.63)
Alpha (Ann.)	-17.85%	-8.59%	9.27%	-10.84%	-5.87%	4.97%	-7.01%	-2.72%	4.29%
Number of Obs.	244			244			244		

Time Window	(-60,-15,15,60)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.129***	1.081***	-0.047	1.080***	1.101***	0.021	0.049	-0.020	-0.069**
	(39.51)	(53.96)	(-1.47)	(38.04)	(54.22)	(0.66)	(0.20)	(-1.24)	(-2.45)
SMB	0.575***	0.429***	-0.146***	0.459***	0.561***	0.102**	0.116	-0.132**	-0.248***
	(5.55)	(9.73)	(-2.61)	(5.73)	(9.78)	(2.11)	(1.61)	(-2.40)	(-4.47)
HML	0.073	0.071	-0.002	0.046	0.001	-0.045	0.027	0.070**	0.043**
	(0.94)	(1.19)	(-0.03)	(0.57)	(0.02)	(-0.49)	(1.41)	(2.00)	(2.41)
Alpha (%)	-0.071	-0.040***	0.032***	-0.062***	-0.053**	0.009	-0.009*	0.013	0.023**
	(-1.47)	(-2.85)	(2.60)	(-2.82)	(-1.98)	(0.11)	(-1.89)	(1.44)	(2.14)
Alpha (Ann.)	-18.19%	-10.14%	8.05%	-15.81%	-13.52%	2.30%	-2.38%	3.38%	5.76%
Number of Obs.	240			240			240		

Time Window	(-180,-15,15,180)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.129***	1.080***	-0.049	1.081***	1.101***	0.020	0.048	-0.021	-0.069***
	(39.70)	(53.66)	(-1.52)	(38.45)	(53.25)	(0.61)	(0.12)	(-1.31)	(-2.65)
SMB	0.577***	0.431***	-0.147	0.458***	0.547***	0.089	0.120	-0.116	-0.236***
	(5.60)	(9.71)	(-1.61)	(5.76)	(9.36)	(0.96)	(1.49)	(-0.88)	(-3.86)
HML	0.068	0.064	-0.003	0.040	-0.007	-0.046	0.028	0.071**	0.043**
	(0.87)	(1.08)	(-0.03)	(0.49)	(-0.12)	(-0.50)	(1.52)	(2.03)	(2.38)
Alpha (%)	-0.083**	-0.051***	0.032***	-0.055*	-0.050*	0.005	-0.028**	-0.001	0.027**
	(-2.37)	(-2.75)	(2.64)	(-1.88)	(-1.91)	(0.19)	(-2.31)	(-0.39)	(2.43)
Alpha (Ann.)	-21.25%	-13.09%	8.16%	-14.03%	-12.75%	1.28%	-7.23%	-0.34%	6.89%
Number of Obs.	240			240			240		

Panel B: Dollar Weight

Time Window	(-30-10,10,30)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.139***	1.138***	-0.001	1.143***	1.130***	-0.013	-0.004	0.008	0.013
	(44.18)	(37.87)	(-0.02)	(42.11)	(36.35)	(-0.44)	(-0.41)	(0.58)	(0.75)
SMB	0.630***	0.470***	-0.160**	0.444***	0.680***	0.236***	0.186***	-0.210	-0.396***
	(8.69)	(5.56)	(-2.05)	(8.90)	(5.08)	(2.78)	(2.62)	(-0.66)	(5.60)
HML	-0.037	-0.127	-0.090	-0.030	-0.187**	-0.157*	-0.007	0.060	0.067
	(-0.52)	(-1.52)	(-1.16)	(-0.40)	(-2.16)	(-1.87)	(-0.24)	(1.54)	(1.44)
Alpha (%)	-0.064**	-0.027	0.037***	-0.029**	-0.006	0.023*	-0.034**	-0.021**	0.014*
	(-2.05)	(-1.01)	(3.81)	(-2.03)	(-1.07)	(1.76)	(-2.02)	(-2.21)	(1.83)
Alpha (Ann.)	-16.23%	-6.80%	9.43%	-7.45%	-1.53%	5.92%	-8.78%	-5.27%	3.51%
Number of Obs.		244			244			244	

Time Window	(-60,-15,15,60)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.117***	1.098***	-0.019	1.091***	1.100***	0.009	0.026	-0.003	-0.029
	(29.26)	(52.88)	(-0.48)	(34.96)	(48.39)	(0.25)	(0.31)	(-0.84)	(-1.46)
SMB	0.541***	0.515***	-0.027	0.519***	0.545***	0.026	0.022	-0.030	-0.052**
	(4.86)	(9.07)	(-0.23)	(5.89)	(8.48)	(0.24)	(0.07)	(-0.13)	(-2.02)
HML	-0.002	-0.091	-0.089	-0.022	-0.144**	-0.122	0.020	0.052**	0.032
	(-0.02)	(-1.51)	(-0.77)	(-0.25)	(-2.22)	(-1.13)	(0.32)	(2.02)	(1.53)
Alpha (%)	-0.055	-0.026**	0.028**	-0.075***	-0.086***	-0.011	0.021	0.060**	0.039***
	(-1.09)	(-2.32)	(2.20)	(-3.80)	(-3.71)	(-0.46)	(0.58)	(2.40)	(3.19)
Alpha (Ann.)	-13.90%	-6.68%	7.22%	-19.13%	-21.89%	-2.76%	5.23%	15.21%	9.98%
Number of Obs.	240			240			240		

Time Window	(-180,-15,15,180)								
	Buy			Sell			Total		
	Before	After	After-Before	Before	After	After-Before	Before	After	After-Before
Mkt	1.112***	1.088***	-0.024	1.089***	1.095***	0.006	0.023	-0.007	-0.030
	(34.26)	(53.35)	(-0.66)	(35.75)	(47.98)	(0.16)	(0.09)	(-0.88)	(-1.51)
SMB	0.573***	0.512***	-0.062	0.510***	0.554***	0.044	0.063	-0.042	-0.106***
	(5.70)	(9.74)	(-0.61)	(5.92)	(8.59)	(0.43)	(0.06)	(-0.76)	(-3.52)
HML	-0.030	-0.095	-0.065	-0.055	-0.159**	-0.104	0.025	0.064**	0.039**
	(-0.33)	(-1.60)	(-0.63)	(-0.63)	(-2.45)	(-1.00)	(0.80)	(2.51)	(2.17)
Alpha (%)	-0.103**	-0.051**	0.053***	-0.075*	-0.046	0.029***	-0.029	-0.005	0.024***
	(-2.46)	(-2.28)	(4.03)	(-1.83)	(-1.51)	(3.58)	(-0.64)	(-0.75)	(2.91)
Alpha (Ann.)	-26.35%	-12.95%	13.40%	-19.00%	-11.73%	7.27%	-7.35%	-1.22%	6.13%
Number of Obs.	240			240			240		