Hard to say goodbye to yesterday: war memories, patriotism, and individual investors' investment preferences

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Abstract

We examine whether memories of interstate wars that occurred long ago, transmitted across generations, affect the stock investment decisions of individuals who never experienced the wars themselves. Using the Second Sino-Japanese War over 1931-1945 as a setting, we find that war memories have a significant impact on individual investors' investment preferences today. Individual investors more affected by the war memories show a stronger preference for Chinese military stocks. The effects are stronger for individual investors residing in cities that experienced more intensive military battles in the War, for older investors who are affected by the war memories to a greater extent, and for those residing in cities with more media exposure about the war memories. Our study contributes to the literature on the role of nonpecuniary preferences, shaped by intergenerational effects, on individual investors' economic decisions.

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1. Introduction

Individuals' preferences are important in shaping economic exchanges, political institutions and policy choices (see Bowles 1998, and Guiso, Sapienza, and Zingales, 2006 for excellent overviews). While economists often focus on pecuniary preferences in analyzing individuals' decision choices, the role of non-pecuniary preferences from psychology has received increased attention (e.g., Corneo and Gruner 2002; Malmendier and Nagel 2011; Bernile, Bhagwat, and Rau, 2017; He, Kothari, Xiao, and Zuo, 2018). People's nonpecuniary preferences could be shaped by a variety of sources: they could arise from an individual's personal experiences such as childhood hardship (the direct sources), but they can also be transmitted from others (the indirect sources), such as school education and the official media (the formal channels) or family and social interactions such as parents to children or peer to peer (the informal channels). The existing economics and finance literature has shown that personal memory (the direct sources) can have a significant effect on individuals' preferences and hence economic decisions (e.g., Malmendier and Nagel 2011; Bernile, Bhagwat, and Rau, 2017; He, Kothari, Xiao, and Zuo, 2018). However, much less is known on the impact of intergenerational transmission of memory, on individuals' *economic* decisions (Becker, 1996; Guiso, Sapienza, and Zingales, 2006).[1] The effect of collective memory on people's decisions could be more important than the effect of individual memory since collective memory provides a sense of identity, unifies a group of members, and can be used to sustain hegemonic power (e.g., Halbwachs, 1925; Loewen, 1999; Fanta, Salek, and Sklenicka, 2019).

The objective of this study is to examine whether the collective memory of large-scale interstate wars that occurred long ago, transmitted across generations, is a

[1] There is a related literature on the impact of indirect sources of preferences on non-economic decisions (e.g., DellaVigna and Kaplan 2007 on political preferences, Alesina and Fuchs-Schündeln 2007 on social policy preferences).

potential indirect source of nonpecuniary preferences that affects the stock investment decisions of individual investors who *never* experienced the wars themselves. The interstate war we focus on is the Second Sino-Japanese War of 1931-1945, one of the largest interstate war conflicts in the world (hereafter referred to as the War).[2] We analyze Chinese individual investors' stock investment decisions during the period 2010-2015. To identify the effect of the war memories on individuals' preferences, we compare the stock investment decisions for individual investors who reside in the Chinese cities that experienced at least one major military battle during the War (the treatment cities) versus individual investors who reside in the other Chinese cities (the control cities).

We argue that the effect of the collective war memories, transmitted across generations, on individuals' preferences should be stronger for those who reside in the treatment cities. First, the treatment cities should have more residents who directly suffered during the War than the control cities. These individuals can transmit their painful war memories to their younger-generation family members and neighbors via vivid story-telling (i.e. the informal channel) (Auerhahn and Laub. 1998; and Felsen, 1998). Second, the local media of the treatment cities (the formal channel) could provide more coverage of the War than those of the control cities, especially during the memorial days. As a result, the residents of the treatment cities who had never personally experienced the War should have a strong personal feeling about the atrocities of the War.[3,4]. On the other hand, the younger generation residents of the

[2] The Mukden incident in September 1931 is widely regarded as the prelude of Japan's invasion of China. The full scale invasion started from 1937. In this paper, we incorporate all major battles during 1931-1945. According to the official PRC statistics, China's civilian and military casualties in the Second Sino-Japanese War were 20 million dead and 15 million wounded ("Remember role in ending fascist war". Chinadaily.com.cn. 2005-08-15. Retrieved 2010-12-02)).

[3] There could be many reasons for the greater local media bias of the treatment cities (Fitch, 2005; Neiger, Meyers, Zandberg, 2011). For example, in our context, reporters of the local media in the treatment cities could have experienced the War directly or the reporters' older-generation family members lived through the War.

control cities are less likely to have such salient memories because fewer individuals in the control cities had the first-hand experience of the War. In addition, due to the physical distance between the treatment cities and control cities, the residents of the treatment cities should find it more difficult to transmit their personal memories or stories of others' experiences to the residents of the control cities (e.g., Park, 1915; Meier, Pierce, Vaccaro, and La Cara, 2016). China's strict household registration system, which restricts the free movement of residents across cities, should further limit the inter-city transmission of such war memories via the indirect sources.

Sociologists have long articulated that collective memories play an important role in human decision making since such memories pass down information and knowledge from generation to generation and thus help avoid the adverse effects of negative events (e.g., Pfister, 2009; Fanta, Salek, and Sklenicka, 2019). Following this theory, we argue that the residents of the treatment cities should have a stronger preference for Chinese military stocks than the residents of the control cities. This is because the defeat of the Chinese armies in the early stage of the War is often attributed to the ill-equipped and poorly trained Chinese military forces.[5] There have also been frequent calls for modernizing China's military forces to avoid similar humiliations in the future.[6] One way for ordinary Chinese people to support such a cause is to hold stocks of publicly listed Chinese companies in the military industry. Therefore, individual Chinese investors may exhibit a strong preference for holding publicly traded Chinese military

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[4] There is a literature on the impact of media bias on political views (e.g., DellaVigna and Kaplan 2007; Gentzkow and Shapiro 2006; Martin and Yurukoglu, 2016). However, few studies have examined the effect of media bias on economic decisions.

[5] The huge gap in military capabilities between Japan and China during the War is better illustrated by the following statistics: Japan produced 1,580 planes, 744 large-caliber artilleries, 330 tanks, 9,500 trucks, and a battleship tonnage of 52,422 annually. In contrast, China had no capacity for producing any of these modern weapons during the first phase of the War In his book Kazutaka Kikuchi (2011) wrote that "at the beginning of the full scale war, the technological supremacy of the Japanese armies was striking … take [the] fighter plane as an example, Japan had 2700 fighter planes but China had only 314. The Japanese army fully controlled the air."

[6] E.g., see http://mil.huanqiu.com/strategysituation/2017-03/10289142.html and http://news.xinhuanet.com/mil/2015-12/24/c_128562623.htm.

stocks as a way to show their patriotism and support for the modernization of China's military forces. Because the residents of the treatment cities have stronger and more vivid memories about the atrocities of the War, they should be more likely to own Chinese military stocks than the residents of the control cities.

There is no doubt that the Second Sino-Japanese War has left permanent scars on the Chinese people who experienced the War first hand. However, it is far from clear whether the War that occurred more than 60 years ago would change the attitudes and preferences of the Chinese people today and whether such altered attitudes and preferences would influence individual investors' actual stock investment decisions, one of their most important economic decisions. First, most of the investors in our sample are born after 1980, long after the end of the Second Sino-Japanese War. Hence, the memories of the War dated more than 60 years ago are fairly remote and hence may have little impact on their stock investment decisions today. Second, our sample individuals' stock investment records are not publicly disclosed and therefore there is little public pressure for individual investors to purchase and hold Chinese military stocks as a show of patriotism.

Our sample includes the stock trading records for a large sample of randomly selected individual brokerage accounts from a major brokerage house over the period 2010-2015. We eliminate the investors born before 1945 in order to make sure none of the individual investors in our sample had direct personal experiences about the War. Consistent with our prediction, we find that individual investors from the treatment cities hold a significantly higher proportion of military stocks in their investment portfolios than individual investors from the control cities. In terms of economic magnitude, the percentage of military stocks in an individual investor's total equity investment portfolio is 9-10% higher for investors in the treatment cities than for investors in the control cities. To control for potential endogeneity of the treatment cities, we also use both 2SLS approach and the propensity score matching approach and find similar inferences.

One could argue that the difference in individual investors' holdings of military stocks for the treatment and the control cities represents the private information advantage of the investors in the treatment cities. To test the validity of this alternative explanation, each month we sort the individual investors in the treatment cities into 10 deciles based on each investor's month-end military stock holding as a fraction of the investor's entire investment portfolio. Then, we compute the abnormal return over the subsequent one-month and three-month periods for the investors in the top decile. We find no evidence that the higher ownership of military stocks by investors in the treatment cities is due to these investors' superior private information advantage.

We conduct three cross-sectional analyses to further demonstrate the effects of war memories. First, if individual investors' higher military stock ownership for the treatment cities is driven by war memories, we should expect the results to be stronger for the treatment cities where the Chinese armies suffered the most casualties. We find evidence consistent with this prediction.

Second, if individual investors' higher military stock ownership for the treatment cities is driven by the inter-generation transmission of painful war memories via vivid story-telling (informal channel), we should expect the results for the treatment cities to be weaker for younger-generation investors due to the decay of war memories. Consistent with this prediction, we find that the difference in the results between the treatment cities and the control cities increases with an individual investor's age. Our results suggest an economically significant intergenerational effect that will take more than 59 years to eliminate.

Third, if individual investors' higher military stock ownership for the treatment cities is partially influenced by the local media (the formal channel), we should expect the results for the treatment cities to be stronger for the treatment cities with higher local media coverage of the War. We find evidence consistent with this prediction.

Rather than using a cross-sectional comparison between the treatment cities and the control cities, we also use an event study approach to identify the effect of war memories. The event is the Diayu Islands (Senkaku in Japanese) incident that occurred during April 2012-September 2012. During this event period, the Japanese government announced several actions that intended to nationalize the Diaoyu Islands. Such actions resulted in a sharp increase in hostility between China and Japan. We conjecture that the nationalization of the Diaoyu Islands should have amplified the difference in the Chinese people's war memories for the treatment cities versus the control cities. Consistent with this conjecture, we find that the proportion of military-stocks in an investor's portfolio increases significantly for the investors residing in the treatment cities relative to those residing in the control cities over the event period relative to the pre-event period or post-event period.

Our paper is related to several streams of literature. First, our paper is related to the growing economics literature that examines the determinants and consequences of individuals' nonpecuniary preferences (Bowles 1998; Guiso, Sapienza, and Zingales, 2006). With regards to determinants of nonpecuniary preferences, many studies in this literature focus on the influences of people's personal experiences (direct sources) on preferences (Malmendier and Nagel 2011; Bernile, Bhagwat, and Rau, 2017). With regard to the indirect sources of nonpecuniary preferences, prior studies have shown the effect of school education and media on people's *social policy* or *political preferences* (e.g., DellaVigna and Kaplan 2007; Gentzkow and Shapiro 2006; Alesina and

Fuchs-Schündeln 2007; Martin and Yurukoglu, 2016; Cantoni et al. 2017). In contrast, we examine the impact of the indirect sources of nonpecuniary preferences on individuals' investment decisions.

There is a growing literature on the relation between early-life experiences and individuals' investment decisions. Kaustia and Knupfer (2008) and Chiang, Hirshleifer, Qian, and Sherman (2011) investigate the effect of prior investment experiences on Initial Public Offering subscriptions. Carroll et al. (2009) seek to link personal experiences to retirement saving behaviors. Relying on the information on households' asset allocations, Malmendier, and Nagel (2011) and Knupfer, Rantapuska, and Sarvimaki (2017) examine how individual experiences of macroeconomic shocks affect financial risk taking. Like these studies, we study individuals' investment decisions. But we differ from these studies in one important aspect: rather than studying the effect of individuals' personal experiences (direct sources of nonpecuniary preferences), we examine the effects of collective memories, an indirect source of individuals' nonpecuniary preferences.

Finally, our work is related to the recent literature on hostility among countries. Prior studies mainly focus on cross-border economic activities. For example, Gupta and Yu (2009) examine the effect of bilateral political relations on trade flows. Guiso, Sapienza, and Zingales (2009) explore the effect of culture aversion. Hwang (2011) studies country-specific sentiment. Fishman, Hamao, and Wang (2014) examine the impact of hostility between China and Japan due to two events in 2005 and 2010 on the stock prices of Japanese companies with high China exposure. Their findings suggest the role of countries' economic and political institutions in mediating the impact of interstate frictions on firm-level outcomes. Our study differs from these studies because we focus on the impact of inter-state hostility on individuals' domestic stock market investment decisions rather than cross-border economic activities. In addition, we study the importance of war memories transmitted across generations rather than the role of formal economic and political institutions.

The rest of the paper is organized as follows. Section 2 introduces the institutional background of the Second Sino-Japanese War. Section 3 explains the data sources and sample selection procedures. Section 4 examines the effect of war memories on individual investors' military stock ownership. Section 5 analyzes the cross-sectional effects of war memories. Section 6 shows an event study based on the nationalization of the Diaoyu Islands. Section 7 concludes.

2. Institutional background

We provide a brief overview of the Second Sino-Japanese War 1931-1945. The Mukden Incident of September 18, 1931, which led to the Japanese army's occupation of Manchuria (i.e., Northeastern China), is widely recognized as the prelude of the full-scale military invasion by Japan. However, during the years 1931-1936, due to the concern over the rise of the Chinese Communist Party (CCP), the Chinese Nationalist Party (Kuomintang, or KMT), the party in control of China, adopted a policy of nonresistance against the Japanese invasion and predominantly focused on the civil war with the CCP. Therefore, there were few major military battles between China and Japan during this period. The full-scale war between China and Japan began in July 1937 after the end of the famous Xi'An Incident that united the KMT and the CCP in the anti-Japanese War.

By 1940 the Japanese army had controlled the entire northeastern coast of China and the areas up to 400 miles inland. Japan's attack on the Pearl Harbor in December 1941 by the Japanese army drew the United States into the World War II. The United

States sent military officers to China and assisted with training and equipping the Chinese armies. The assistance from the United States helped narrow the gap in military-capability between China and Japan. The Second Sino-Japanese War came to an end in August 1945, after the United States dropped two nuclear bombs over Hiroshima and Nagasaki.

Throughout the Second Sino-Japanese War, the Chinese armies engaged with the Japanese army in many military battles on Chinese soil. Following Guo (2005) and Zhang (2007), we identify 34 major battles during the War between September 1931 and August 1945. Appendix A shows the basic information about each battle and the corresponding officially reported mortality numbers on both sides. Appendix B also plots the geographic locations of these battles on the map. It is clear that the 34 major battles scattered across many parts of China.

The human casualties from the Second Sino-Japanese War were very high. As noted above, many Chinese soldiers lost their lives in the military battles. Even more Chinese civilians were killed or injured during the War (see footnote 2). The War also left significant and long lasting psychological scars among the living Chinese people who personally experienced the atrocities of the War. In addition, the War caused substantial damages to many Chinese cities and regions. Prime farming areas were ravaged in the battle fighting. Millions of people were rendered homeless by the destruction of towns and cities all over China.

3. Data sources and sample selection procedures

We obtain the raw data on individual investors' brokerage accounts from one of the largest nationwide brokerage houses in China under the condition of anonymity. The raw data contain an investor's demographic information (age, gender, residential address at the city level, and the name of the brokerage branch where an investor opens the account), the brokerage account ID, an individual stock's trading date, trading type (open market buy or sell), security type (A or B share), the quantity of a trade, the dollar value of a trade, and trading commission. Our research question requires the monthly balance of each individual stock held by each individual investor account. Unfortunately, such data are not directly available from the raw data. Instead, we have to reconstruct individual stocks' monthly balances using each account's stock transaction records from the opening of the brokerage account.

To reduce data collection costs, we start with 216,732 unique brokerage accounts opened between January 1, 2010, and April 30, 2012. From these brokerage accounts we select a random sample of 75,045 (about one third) unique brokerage accounts and obtain all the stock transaction records of the selected accounts from the beginning of each account up to December 31, 2015. Hence, the maximum sample period for our brokerage accounts covers January 1, 2010, to December 31, 2015.

Table 1 reports our sample selection procedures for the individual brokerage accounts starting from the raw data provided by the brokerage house. We impose several important sample selection restrictions. First, we drop the dormant accounts that never traded over the period from the account opening to December 31, 2015 (29% of the 75,045 selected accounts). Second, we drop the institutional accounts (0.1% of the 75,045 selected accounts) because our focus is individual investors. Third, we drop the brokerage accounts if an investor lives in city A but opens the account in a different city B, even though the brokerage house has a branch in city A at the time of the investor's account opening (3.8% of the 75,045 selected accounts). There are many possible reasons for why this occurs, including the possibility that the investor has moved, or the investor's account has been lent to someone else for illegal trading.

Fourth, we drop the accounts if an investor's age is larger than 65 (i.e. born before 1945) since they directly experienced the War. The final sample after imposing these sample restrictions contains 48,525 unique individual investor accounts, including 30,118 accounts for the treatment cities and 18,407 accounts for the control cities.

We obtain the stock price and other firm-specific information from the China Stock Market and Accounting Research Database (CSMAR). We also obtain macroeconomic information from the WIND database.[7]

4. Effect of war memories on individual investors' military stock ownership

4.1. Research design

We use the following OLS regression model to test the effect of war memories transmitted across generations on individual investors' military stock ownership:

$$HR\ (Mil)_{j,t} = a_0 + a_1 \times Treatment_j + a_2 \times X_{j,t} + a_3 \times \delta_{year\text{-}month} + a_4 \times \theta_{province} + \varepsilon_{j,t} \quad (1)$$

The unit of observation is an investor (j) month (t). To create the sample needed for model (1)'s estimation, we start with the final sample of 48,525 unique individual investors' brokerage accounts in Table 1. We cumulate each individual account's stock transactions from the opening of the account to obtain the month-end balance of the account. We allow an account's month-end balance to be zero. However, a zero month-end balance could also mean that an investor is no longer interested in stock investments (i.e., inactive accounts). To rule out this possibility, we require the investor months with zero month-end balances to have at least one stock transaction during the month. Our sample for model (1) has 1,641,559 investor-month observations, representing 48,525 unique accounts. Due to stock market trading suspensions, some of the investor months have missing values, resulting in a final

[7] Information about city-level macro-economic conditions is largely unavailable and therefore we rely on province-level data instead.

usable sample of 1,619,630 investor-months for 48,516 unique accounts.

$HR(Mil)_{jt}$ is the monthly balance of investor *j*'s military-stock holding as a fraction of the investor's entire stock portfolio at the end of month *t*. *Treatment* is a dummy variable that equals one if an investor lives in a city that once experienced one of the major military battles during the Second Sino-Japanese War 1931-1945, and zero otherwise. The coefficient on *Treatment* captures the effect of war memories transmitted across generations on individual investors' preference for military stocks.

Prior research (e.g., Barber and Odean, 2001; Goyal, 2004; Feng and Seasholes, 2005, 2008) find that investors' personal characteristics affect their investment decisions. Hence, to rule out potential alternative explanations, we include a set of such control variables ($X_{j,t}$), including individual investor j's age, gender, risk preference, trading frequency, and trading experience. All investors' personal characteristics are provided by the brokerage house based on each investor's supplied information at the account opening or trading behavior since the account opening. In addition, we also control for region-level control variables, including province quarterly GDP and province yearly unemployment rate. We also include year-month and province fixed effects to control for time fixed effects and province-level fixed effects.

4.2. Descriptive statistics and regression results

Panel A of Table 2 reports the distributions of the demographic variables for the treatment and control cities. The treatment and control samples are significantly different from each other on all dimensions, suggesting that it is important to control for these variables in regression model (1). Panel A of Table 3 reports the summary statistics for the full sample. The average holding ratio of military stocks is 3.91% for the full sample. Note that the standard deviation of the holding ratio of military stocks is 16.62%, implying a large variation in investors' preferences for these stocks. The age of an average sample is around 38, indicating that the majority of investors in our sample belongs to the post-war generation one or two.

The first column of Table 4 shows the OLS regression results of model (1) using the full sample of 48,516 unique individual investor accounts. Standard errors are clustered by city and year-month. Consistent with our prediction, the estimated coefficient on *Treatment* is positive and significant (0.345, t = 6.91), suggesting that investors from the treatment cities allocate a disproportionally large percentage of their portfolios to military stocks. Many of the control variables are significant.

4.3. Instrumental variable regression approach

One potential concern about model (1) is that *Treatment* could be correlated with omitted variables. To address this endogeneity concern, we adopt two complementary approaches: (i) an instrumental variable approach in this section; and (ii) a propensity score matching approach in the next section.

We use the geographic proximity between a city and the nearest major iron ore mine found before the Second Sino-Japanese War as an instrumental variable (denoted as *Distance*). As one important strategic goal of the Japanese army in the War was to control the mineral resources in China (Yukio, 1995), the cities closer to the major iron ore mines were more likely to experience military conflicts during the War. Therefore, *Distance* should be negatively correlated with *Treatment* (the relevance condition of a valid instrument). In addition, we argue that *Distance* should satisfy the exclusion condition of a valid instrument because there is no reason to expect *Distance* to be correlated with the omitted determinants of HR (Mil) contained in model (1)'s error term.

Columns (2) and (3) of Table 4 show the 2SLS regression results of model (1). As predicted, the coefficient on *Distance* is significantly negative in the first stage regression. More importantly, the coefficient on *Treatment* continues to be significantly positive in the second stage regression.

4.4. Propensity-score matching approach

To better match the investors in the treatment cities with the investors in the control cities on investor characteristics, we also adopt a propensity score matching (PSM) approach. Specifically, we use the following logit model to compute the propensity scores:

$$Logit(Treatment{=}1)_j = a_0 + a_1 \times Male_j + a_2 \times Risk\ dummy_j + a_3 \times Age_j + a_4 \times High\ trading\ dummy_j + a_5 \times Account\ Open\ month_j + \varepsilon \quad (2)$$

The unit of observation is an investor *j*. The matching variables are the five individual investor demographic characteristics included in model (1) except that we use *Account Open month* instead of *Experience*.

We match each investor in a treatment city with the investors in the control cities without replacement as long as the difference in the propensity scores between a treatment observation and control observation is smaller than 0.001. The propensity score matched sample contains 30,410 unique brokerage accounts (1,033,702 investor-months), including 15,211 accounts for the treatment cities and 15,199 accounts for the control cities.

Panel B of Table 2 reports the distributions of the demographic variables for the treatment and control cities after the match. While the treatment and control samples are significantly different from each other on all dimensions in Panel A of Table 2, the differences are insignificant after the match in Panel B. We further plot the Kernel density for the two continuous demographic characteristics: *Age* and E*xperience* in Figure 1. It shows that the treatment and control groups have close density distribution in terms of the two continuous matching variables, age, and experience, after the match. Panel B of Table 3 reports the summary statistics of the regression variables of model (1) for the matched sample.

Column (4) of Table 4 shows the regression results of model (1) using the propensity score matched sample. The coefficient on *Treatment* is still significantly positive. The magnitude of the coefficient suggests that investors in the treatment cities hold around 10%(=0.378/3.92)) more military-stocks than investors in the control cities. Since the inferences reported in Table 4 before versus after the propensity score matching are similar, we will use the smaller but better matched sample of treatment and control cities in the following analyses.

The propensity score matching approach is based on investors' demographic characteristics. As a further refinement of our matching approach, we employ an adjacent city matching method. In particular, we require the matched pairs of the treatment cities and control cities in the propensity score matched sample to satisfy the following conditions: (i) the treatment and the control cities are located in the same province; (ii) the economic distance (measured using the GDP in 2009, one year before the beginning of our sample period) between the treatment and control cities is the closest; and (iii) the physical distance between the treatment and control cities is the closest. These three additional matching criteria ensure that the investors in the treatment cities and control cities are much more comparable in not only personal characteristics but also social and economic environments.

We are not able to find control cities for three treatment cities, Beijing, Shanghai, and Tianjin since they are municipalities directly under the Central Government's control. Thus, the investors in these treatment cities are excluded from this analysis. Our final sample contains 23 pairs of treatment and control cities, representing 9,736 unique investors for the PSM sample. We control for the treatment-control pair fixed effects to eliminate cross-pair variations.

The regression results are reported in the last column of Table 4. We find that the coefficient on *Treatment* is significantly positive (0.759, t = 8.93), consistent with the PSM regression results in column (4) of Table 4.

4.5. Informed trading as an alternative explanation

One potential alternative explanation for the regression results in Table 4 is that the higher military stock ownership in the portfolios of investors in the treatment cities reflects these investors' private information about the military stocks. To check the validity of this alternative explanation, we examine the future abnormal return performance of the military stock ownership for the investors in the treatment cities. To do so, each month we sort all investors in the treatment cities into 10 deciles based on their month-end $HR\ (Mil)_{jt}$. Then, we estimate the size-adjusted buy-and-hold abnormal portfolio return of the military stock holdings for the top decile investors in the next one month and three months. We find that the military stock ownership for an investor in the top decile can be still small. To increase the test power, we also compute the abnormal portfolio return of the military stock holdings for the top decile investors whose $HR\ (Mil)_{jt}$ is at least 1% or 10%.

The results are reported in Table 5. We find that the signs of the abnormal returns are negative for both the investors in the top decile and the investors in the top decile with material military stock ownership in their portfolios.[8] Overall, we find no evidence consistent with the alternative explanation.

5. Cross-sectional analysis of individual investors' military stock ownership

To further demonstrate the impact of war memories on individual investors' military stock ownership, we perform three cross-sectional regression analyses in this section: (i) military battle intensity in section 5.1; (ii) age effect in section 5.2; and (iii) local media effect in section 5.3.

5.1. The intensity of the war memories

As shown in Appendix B, the intensity of the battles included in the treatment cities varies significantly across cities. In this section, we examine whether the documented treatment effect in model (1) is stronger for the treatment cities with more Chinese military casualties. We argue that the more intensive a battle is in terms of casualties, the more likely that the atrocities of the war memories will be transmitted to the younger generations via both formal and informal channels.

Column (1) of Panel A in Table 6 shows the regression results of this hypothesis test, using the investor months for the treatment cities only. Because each battle has both Chinese and Japanese casualties, we include both in the same regression. In addition, we scale the casualties by the size of the battlefield because of the significant variation in the scale of each battle. Our hypothesis would predict the coefficient on *Chinese army mortality/km2* to be significantly positive. However, we do not make a prediction on the coefficient on *Japanese army mortality/km2* because the death of Japanese soldiers is unlikely to arouse sad feelings and emotions among

[8] The significance levels of the 3-month abnormal returns should be interpreted with caution because we have not adjusted for potential dependence of the returns across the overlapping months. But this fact should not affect our inference because the mean abnormal returns are all negative.

Chinese investors. Consistent with our prediction, the coefficient on *Chinese army mortality/km2* is significantly positive. We find that the coefficient on *Japanese army mortality/km2* is negative but insignificant. In column 2, we exclude the variable of *Japanese army mortality/km2* from the specification and find a qualitatively similar result.

5.2. The age effect

One important element in the process of shaping collective memories is the story-telling through which information and knowledge are passed down by older generations. However, such an inter-generational transmission of war trauma inevitably fades as time goes by (Ebbinghaus, 1913; Auerhahn and Laub. 1998; and Felsen, 1998). Hence, we expect the effect of the collective war memories to become weaker over each successive generations. In other words, we predict the effect of *Treatment* for model (1) to increase with an investor's age.

Panel B of Table 6 shows the regression results of this prediction. Because of the introduction of the interaction effect *Treatment* × *Age*, we an afford to include the city fixed effects rather than the coaser province fixed effects. Consistent with our prediction, the coefficient on *Treatment* × *Age* is positive and significant (0.013, t = 7.8). Since the coefficient on *Treatment* is insignificantly different from zero, the results suggest that, under the strict assumption of linearity, it takes around 59 years ((2010-1945)-0.081/0.013) for the difference between the treatment cities and control cities to disappear completely, suggesting an economically significant intergenerational effect.[9] In the second column, we further separate the sample into two groups based on whether an individual is the first post-war generation (i.e. born

[9] 2010 is the starting year of our sample. 1945 is the end of the Second Sino-Japanese War.

between 1945-1970) or the second post-war generation (i.e., born after 1970). We find that, for individuals residing in treatment cities, the first post-war generation holds 9.2% more military-stocks than the second post-war generation.

5.3. *The local media effect*

The prior literature shows that media has a distinctive role in shaping collective memories (e.g., Neiger, Meyers, Zandberg, 2011). Hence, we examine the role of media in reviving the collective war memories and its resultant effect on individuals' investment decisions. Since the national media affects all Chinese investors, we focus on the role of local media on individual investors' military ownership decisions.

We define the local media's coverage of the war memories (denoted as *High Media*) using the following steps. First, for each city included in our sample, we identify the most widely circulated local party newspaper and local non-party newspaper from a popular newspaper database, WISENEWS.[10] Second, we identify all the articles whose titles contain any of the following keywords: anti-Japanese, patriotic, anti-war, Second World War, Sino-Japanese. Third, we manually read the identified articles and exclude irrelevant articles (e.g., those articles may be related to economics, culture, sanitation, sports, etc.). Finally, we compute the total number of war memory related articles reported by the two local newspapers for each city-year and use it as for the proxy for local residents' exposure to the propaganda aimed at reviving the war memories. *High Media* is one if the total number of war memory related articles in the past three years is above the sample median in a year and zero otherwise.[11]

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[10] 12% of the cities are not covered by WISENEWS. For these cities, we use the provincial newspapers instead.
[11] To verify the accuracy of our selection procedures, we manually read all the news articles over a randomly selected 7-day period and count the total number of war-relevant articles. We compare the

Panel C of Table 6 presents the yearly average number of war memory related news by the local media for both treatment and control cities. Consistent with the notion of local media bias (Kitch, 2005; Neiger, Meyers, Zandberg, 2011), we find that local media in treatment cities report 21.31 more war-relevant articles per year than those in the control cities. This finding suggests that local media is an important force reflecting and shaping the local collective war memories.

Panel D in Table 6 presents the regression result. Consistent with our expectation, the coefficient on *High Media×Treatment* is significantly positive, suggesting that individual investors residing in treatment cities with more frequent local media coverage of the war memories exhibit a stronger preference for military stocks.

Panel E of Table 6 combines both interaction effects in Panels B and D into one single model. Again, the coefficients on the interaction terms, *Age×Treatment*, *Treatment×First post-war generation*, and *High Media×Treatment* continue to be significantly positive.

6. Event study based on the nationalization of the Diaoyu Islands

Our basic regression model (1) is cross-sectional in nature. Hence, readers could be still concerned that our previous results are due to correlated omitted factors. To more directly show the causal relationship between the war memories transmitted across generations and individual investors' preference for military stocks, we explore Japan's nationalization of the Diaoyu Islands in 2012 as an exogenous shock.

The Diaoyu Islands is a focal point in the China-Japan relationship. China claims the discovery and ownership of the islands, whereas Japan regards the islands as part of the city of Ishigaki. Although the Japanese government has not allowed the Ishigaki

result with that based our filtering scheme. The comparison shows that our filtering scheme can effectively identify more than 95% of all relevant articles.

administration to develop the Islands, it attempted to nationalize the Islands via a series of public actions from April 2012 to September 2012. The Chinese government confronted Japan over a series of actions. General Xu Caihou, in particular, advised the Chinese military to prepare for any act of war, and drones were sent to the Islands.

We argue that the sudden increase in the hostility between China and Japan due to the nationalization of the Diaoyu Islands should have intensified the Chinese people's memories of the Second Sino-Japanese War. In addition, this effect should be stronger for the residents of the treatment cities due to their stronger war memories transmitted across generations. Therefore, we predict the nationalization of the Diaoyu Islands to lead to a greater increase in the preference for military-stocks for the investors of the treatment cities than for the investors of the control cities.

We test this prediction using the following difference-in-differences regression model:

$$HR\ (Mil)_{j,t} = a_0 + a_1 \times Treatment_j \times React\text{-}period_t + a_2 \times Treatment_j \times Post\text{-}react\text{-}period_t + a_3 \times X_{j,t} + \delta_{year\text{-}month} + \lambda_{individual} + \varepsilon_{j,t} \quad (3)$$

Our key variable of interest is $Treatment_j \times React\text{-}period_t$. $React\text{-}period_t$ is a dummy variable that equals one for the period when Chinese investors reacted to Japan's nationalization of the Diaoyu Islands and zero otherwise. The nationalization of the Diaoyu Islands was first proposed in April 2012 and completed in September 2012.[12] Hence, $React\text{-}period_t$ is one for the six months spanning April 2012-September 2012 and zero otherwise. We choose two benchmark periods for the reaction period. The first period is the six months immediately prior to the reaction period while the second period is the six months immediately after the reaction period.

[12] On 16 April 2012, Tokyo's prefectural governor Shintaro Ishihara publicly announced his decision to let Tokyo Municipality purchase the island from its private owner. On 19 August, China's Ministry of Foreign Affairs strongly protested to the Japanese Ambassador to China. On September 10, 2012, the Japanese government "purchased" Diaoyu Island and its affiliated Nanxiao Island and Beixiao Island.

Post-react-period$_t$ is a dummy variable that equals one for the six months following the reaction period and zero otherwise.

We control for individual investor fixed effects and time (year-month) fixed effects in the model (3). X is the same as in model (1). Due to including investor fixed effects, investors' demographic characteristics are redundant in the model (3).

The results are reported in Panel A of Table 7. Standard errors are clustered by city and year-month. Consistent with our prediction, the coefficient on *Treatment*$_j$ × *React-period*$_t$ is positive and significant, suggesting that investors in the treatment cities purchased significantly more military stocks during the Diaoyu Islands dispute period (0.185, t = 2.27). Interestingly, the coefficient on *Treatment*$_j$ × *Post-React-period*$_t$ is insignificant, suggesting that the increase in the ownership of military stocks by the investors of the treatment cities is transitory. In Panel B, we mirror the tests in Table 5 and examine whether the increase in holdings of military-stocks is driven by private information. We find an insignificant effect.

Overall, our results in Table 7 provide further evidence supporting our hypothesis that the war memories transmitted across generations induce investors in the treatment cities to show a stronger preference for military stocks.

7. Conclusion

The economics literature has shown a growing interest in understanding the role of nonpecuniary preferences from psychology in individual investors' economic decisions. People's nonpecuniary preferences could be affected by a variety of sources. They could arise from an individual's personal experiences (the direct sources), but they can also be transmitted from others (the indirect sources), such as the official media (the formal channels) or family and social interactions such as parents to children or peer to peer (the informal channels). Prior research has shown the importance of direct sources of nonpecuniary preferences on individuals' economic decisions. The objective of this study is to contribute to this literature by showing one important indirect source of nonpecuniary preferences, war memories transmitted across generations.

We use the Second Sino-Japanese War 1931-1945 as our proxy for the war memories and examine whether such war memories transmitted across generations affect the investment decisions during the period 2010-2015 for individual investors who never personally experienced the War. To identify the effect of the war memories on individuals' preferences, we compare the stock investment decisions for individual investors who reside in the Chinese cities that experienced at least one major battle during the War (the treatment cities) versus individual investors who reside in the other Chinese cities (the control cities).

Our results show that individual investors in the treatment cities exhibit a stronger preference for owning Chinese military stocks than investors in the control cities. This effect is more pronounced for the treatment cities that saw higher Chinese military casualties during the Second Sino-Japanese War, older investors who are likely to have stronger memories about the War, and for cities where the local media have more discussions on the Sino-Japan war conflicts. We use Japan's attempted nationalization of the Diaoyu Islands in 2012 as an exogenous event to further identify the effect of the collective war memories on treatment city investors' preference for military stocks. Overall, these results suggest that the collective memories of wars that occurred long ago, transmitted across generations, can have a significant and long lasting impact on the investment decisions of individual investors today.

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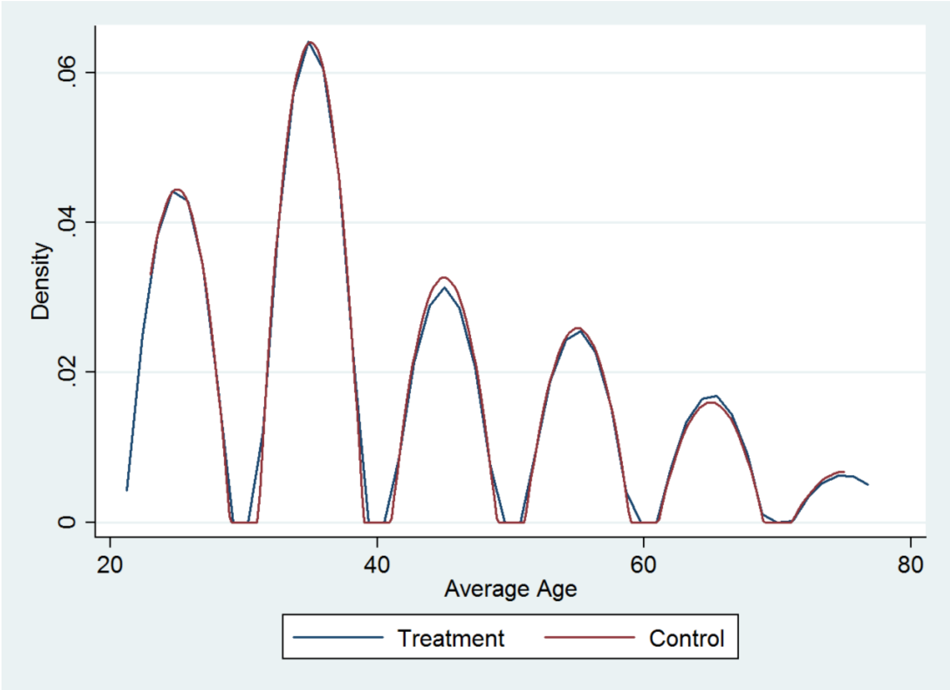
Figure 1 Kernel density of demographics in the matched sample

This figure shows the kernel density of the distributions of demographics in the matched sample. *Treatment* refers to the account holders whose resident city suffered battles during the China-Japan War. Control refers to the account holders whose resident city did not have historically widespread battles during the China-Japan War. *Average Age* is the mean value of age range that the account holder ticks when opening the account. *Average Experience* is the average value of the account holder's trading experience in our sample period from 2010 to 2015.



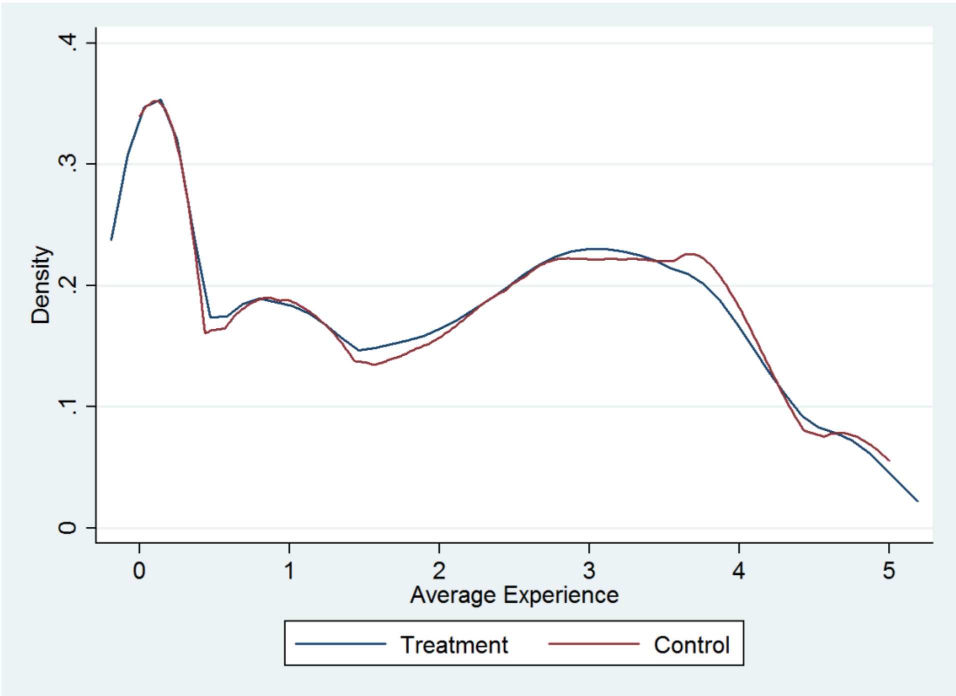


Table 1: Sample Selection Procedures

Sample Selection Procedures	# of individual investors
Total # of account opened between January 2010 and April 2012	216,732
Randomly draw around 1/3 sample to obtain trading information	75,045
we drop the dormant accounts that never traded over the period from the account opening to December 31, 2015	-22,392
Drop the institutional accounts	-77
Drop the accounts if an investor resides in city A but opens the account in a different city B, even though the brokerage house has a branch in city A at the time of the investor's account opening	-2,848
Drop if investor's age>65 (i.e. born after 1945)	-1,203
Final sample	48,525
Final sample after propensity score matching	30,410

Table 2: Individual characteristics

This table presents the individual characteristics for treatment and control individuals (unit: a person), respectively. The sample is based on individual investors that opened a trading account during 2010.1 to 2012.4. In panel A, we present the comparison based on the full sample. Panel B presents the comparison based on one-to-one propensity score matched sample. Our matching algorithm is based on gender, risk preference, average age, trading frequency dummy and account opening month between treatment and control groups. *See Appendix A for definitions of the variables.*

Panel A. Comparison of demographics in the full sample

		Control		Treatment			
		Mean	std.dev	Mean	std.dev	Diff	T-value
Full sample	Male	0.547	0.498	0.532	0.499	0.015***	3.306
	Risk dummy	0.010	0.099	0.020	0.140	-0.010***	-9.470
	Avg(Age)	36.116	12.318	38.591	13.718	-2.475***	-20.840
	High trading dummy	0.608	0.488	0.553	0.497	0.055***	12.058
	Avg(Experience)	1.933	1.542	2.185	1.525	-0.252***	-17.815
	# of Obs	30118		18407			

Panel B. Comparison of demographics in propensity score matched sample

		Control		Treatment			
		Mean	std.dev	Mean	std.dev	Diff	T-value
Matched Sample	Male	0.543	0.498	0.538	0.499	0.005	0.821
	Risk dummy	0.006	0.077	0.006	0.076	0.000	0.297
	Avg(Age)	36.756	12.318	36.763	12.481	-0.007	-0.050
	High trading dummy	0.580	0.494	0.582	0.493	-0.002	-0.392
	Avg(Experience)	2.071	1.529	2.052	1.525	0.020	1.132
	# of Obs	15119		15211			

Table 3: Summary statistics

This table shows the summary statistics of the full regression sample (unit: person-month) and the regression sample based on propensity score matching, respectively. *See Appendix A for definitions of the variables*

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Panel A. Summary statistics of full regression sample

	Obs	Mean	Std.dev	Min	P50	Max
Mil holding ratio (%)	1619630	3.96	16.62	0	0	100
JP holding ratio (%)	1619630	7.17	22.14	0	0	100
Treatment	1619630	0.42	0.49	0	0	1
Risk dummy	1619630	0.02	0.12	0	0	1
Age	1619630	38.17	11.96	18	34	65
High trading dummy	1619630	0.61	0.49	0	1	1
Male	1619630	0.52	0.50	0	1	1
Experience	1619630	2.41	1.55	0	2	5
Province yearly unemployment rate	1619630	3.10	0.83	1.21	3.17	4.47
Province quarterly GDP (Unit:1T)	1619630	1.73	1.37	0.03	1.37	7.28

Panel B. Summary statistics of propensity score matched sample

	Obs	Mean	Std.dev	Min	P50	Max
Mil holding ratio (%)	1033702	3.92	16.47	0	0	100
JP holding ratio (%)	1033702	7.72	23.06	0	0	100
Treatment	1033702	0.53	0.50	0	1	1
Risk dummy	1033702	0.01	0.08	0	0	1
Age	1033702	37.82	11.66	18	34	65
High trading dummy	1033702	0.61	0.49	0	1	1
Male	1033702	0.52	0.50	0	1	1
Experience	1033702	2.40	1.55	0	2	5
Province yearly unemployment rate	1033702	3.05	0.88	1.21	3.13	4.47
Province quarterly GDP (Unit:1T)	1033702	1.72	1.36	0.03	1.37	7.28

Table 4: Collective war memories and military stock holdings

This table shows the effect of collective war memories on military-related stock holdings. The sample period is from 2010.1-2015.12. We conduct the analyses on the individual-month level. Column (1) shows the baseline regression result. Columns (2)-(3) show the 2SLS test using the geographic distance between a city and the closest iron ore mine before the war as IV. Column (4) shows the result based on the propensity score matched sample. Column 5 shows the result based on the adjacent city matched sample. Province and year-month fixed effects are included. Standard errors are clustered by city and year-month and clustering-corrected t-statistics are reported in parentheses. We use ***, **,* to indicate significance at 1%, 5%, 10% level respectively. See Appendix A for definitions of the variables.

	(1)	(2)	(3)	(4)	(5)
	Full sample	First stage	Second stage	Propensity score matched sample	Pair-city matched sample
VARIABLES	Mil holding ratio (%)	Treatment	Mil holding ratio (%)	Mil holding ratio (%)	Mil holding ratio (%)
Treatment	0.345***			0.378***	0.502***
	(6.32)			(5.59)	(9.06)
Distance		-0.001***			
		(-15.49)			
Fitted(Treatment)			3.130***		
			(12.75)		
Age	0.007***	0.001***	0.005***	0.004***	0.015***
	(5.71)	(19.59)	(3.89)	(2.93)	(6.81)
Risk dummy	-0.223**	0.016***	-0.265***	1.411***	-0.982***
	(-2.39)	(9.52)	(-2.85)	(6.86)	(-6.04)
High trading dummy	-0.293***	-0.003***	-0.285***	-0.119***	-0.473***
	(-9.77)	(-7.81)	(-9.47)	(-3.27)	(-9.14)
Male	-0.031	-0.006***	-0.014	-0.021	0.106**
	(-1.14)	(-13.08)	(-0.52)	(-0.55)	(2.48)
Experience	-0.160***	0.019***	-0.190***	-0.158***	-0.023
	(-5.41)	(5.11)	(-6.41)	(-3.95)	(-0.43)
Log(Province quarterly GDP)	0.981***	0.017	0.925***	1.586***	2.098***
	(3.47)	(0.40)	(3.28)	(4.60)	(3.40)
Province unemployment rate	0.022	-0.006	0.040	0.108	1.033***
	(0.34)	(-0.54)	(0.62)	(1.61)	(10.29)

Constant	5.084***	0.150**	8.790***	5.598***	-2.081**
	(18.75)	(2.17)	(9.79)	(18.85)	(-2.46)
Fixed Effects	Province, year-month	Province, year-month	Province, year-month	Province, year-month	Province, year-month
Observations	1,619,630	1,619,630	1,619,630	1,033,702	411,168
R-squared	0.002	0.828	0.002	0.002	0.002

Table 5: Military stock holdings and abnormal returns

This table shows the military stock portfolio return for the treatment group with the highest level of military stock holding. For each month, we divided the treatment sample into 10 deciles according to their military stocks' holding, where 10^{th} decile is the sample with the highest level of military stocks' holding. We use ***, **, * to indicate significance at 1%, 5%, 10% level respectively. See Appendix A for definitions of the variables.

	Mil holding ratio in 10^{th} decile		Mil holding ratio(%)>1% & in 10^{th} decile		Mil holding ratio(%)>10% & in 10^{th} decile	
	Mean	T-value	Mean	T-value	Mean	T-value
Next 1 month weighted average BHAR (Mil Portfolio)	-0.002***	-4.029	-0.002***	-4.482	-0.002***	-4.158
Next 3 month weighed average BHAR (Mil Portfolio)	-0.001	-0.839	-0.001	-1.332	-0.001	-1.496

Table 6: Cross-sectional analyses of individual investors' military stock ownership

Panel A shows the effect of military casualty intensity on military stock holdings. Panel B shows the effect of an investor's age on military stock ownership. Panel C shows the degree of local media bias. Panel D shows the effect of local media coverage of the War on military stock holdings. The sample period is from 2010.1-2015.12 Province and year-month fixed effects are included in Panel A. City and year-month fixed effects are included in Panels B and D. Standard errors are clustered by city and year-month and clustering-corrected t-statistics are reported in parentheses. We use ***, **, * to indicate significance at 1%, 5%, 10% level respectively. See Appendix A for definitions of the variables.

Panel A. Effect of military casualty intensity

	(1)	(2)
VARIABLES	Mil holding ratio (%)	Mil holding ratio (%)
Chinese army mortality/ km2	0.014*	0.012***
	(1.93)	(4.94)
Japanese army mortality/km2	-0.014	
	(-0.28)	
Other Controls	Yes	Yes
Fixed Effects	Military Capital, Province, year-month	Military Capital, Province, year-month
Observations	543,402	543,402
R-squared	0.001	0.001

Panel B. Age effect

	(1)	(2)
VARIABLES	Mil holding ratio (%)	Mil holding ratio (%)
Age ×Treatment	0.012***	
	(4.59)	
Age	-0.003	
	(-1.22)	
First post-war generation ×Treatment		0.380***
		(5.93)
First post-war generation		-0.080
		(-1.62)
Other Controls	Yes	Yes
Fixed Effects	City, year-month	City, year-month
Observations	1,033,702	1,033,702
R-squared	0.004	0.004

Panel C. Local media bias

	N (unique city)	Mean	Std	Min	p25	p50	p75	Max
Yearly average # of war related news articles in all cities	345	26.27	24.86	0	12	20	34	263
Yearly average # of war related news articles in treatment cities	72	43.13	40.56	0	20	31.75	49	263
Yearly average # of war related news articles in control cities	273	21.82	16.04	0	11	18	30	116
Diff (Treatment-Control)		21.31***						

Panel D. Local media effect

VARIABLES	(1) Mil holding ratio (%)
Highmedia dummy×Treatment	0.417***
	(3.39)
Highmedia dummy	0.052
	（0.61）
Other Control	Yes
Fixed Effects	City, year-month
Observations	944,065
R-squared	0.003

Panel E. Local media effect and age effect in one model

VARIABLES	(1) Mil holding ratio (%)	(2) Mil holding ratio (%)
Treatment×Highmedia dummy	0.408***	0.403***
	(3.32)	(3.28)
Treatment×Age	0.015***	
	(5.12)	
Treatment×First post-war generation		0.398***
		(5.78)
Highmedia dummy	0.063	0.058
	(0.73)	(0.67)
Age	-0.006**	
	(-2.37)	
First post-war generation		-0.113**
		(-2.04)
Other Control	Yes	Yes
Fixed Effects	City, year-month	City, year-month
Observations	944,065	944,065
R-squared	0.003	0.003

Table 7 Effects of Diaoyu Island Dispute

This table shows the effects of Diaoyu Island dispute on military stock holding. Panel A presents a difference-in-difference analysis based on the event window. Panel B presents the performance of military stock holding. Diaoyu Island dispute is first announced in 2012.4 and is further processed in 2012.9. The Pre-react-period is defined as from 2011.10-2012.3; React-period is defined as from 2012.4-2012.9; Post-react-period is defined as from 2012.10-2013.3. Individual and year fixed effects are included. Standard errors are clustered by city and year-month and clustering-corrected t-statistics are reported in parentheses. We use ***, **, * to indicate significance at 1%, 5%, 10% level respectively. See Appendix A for definitions of the variables.

Panel A. Effect of Diaoyu Island Dispute on military stock holdings

VARIABLES	Mil holding ratio (%)
Treatment×React-period	0.200**
	(2.28)
Treatment×Post-react-period	-0.021
	(-0.25)
Log(Province quarterly GDP)	-1.140***
	(-2.65)
Province unemployment rate	0.249***
	(2.84)
Constant	4.215***
	(11.27)
Fixed Effects	Individual, year-month
Observations	312,289
R-squared	0.702

Panel B. Performance of military stock holding

VARIABLES	Next 1 month weighted average BHAR (Mil Portfolio)	Next 3 month weighted average BHAR (Mil Portfolio)
Treatment ×React-period	-0.002	-0.003
	(-0.51)	(-0.51)
Treatment ×Post-react-period	-0.002	-0.002
	(-0.64)	(-0.26)
Log(Province quarterly GDP)	0.014	0.020
	(0.80)	(0.67)
Province unemployment rate	0.004	0.006
	(1.24)	(1.11)
Constant	-0.055***	-0.071***
	(-4.12)	(-2.88)
Fixed Effects	Individual, year-month	Individual, year-month
Observations	25,654	25,654
R-squared	0.265	0.346

A. Variables and Definitions

Mil holding ratio	Military stocks holding ratio is computed as the total market value of military stocks held by the individual at the end of the month and divided by total market value of all the stocks held at the end of the month. Market value is computed as month-end stock price multiplied by the number of shares.
Chinese (Japanese) army mortality per km^2	The total number of the Chinese (Japanese) army death divided by the area of city (unit: km2).
Male	Dummy variable equals 1 if the account holder is a male and 0 otherwise.
Age	The age of the account holders.
Risk dummy	Dummy variable equals 1 if the account holder is classified as a risk lover according to the mandatory risk assessment.
High trading dummy	Information provided by the brokage firm
Experience	The number of years of trading since the date of account opening.
Province yearly unemployment rate	Yearly unemployment rate at the province level.
Province quarterly GDP	Quarterly GDP for each province.
CSI300 market index	Highly cited market index for A-share market in China
Market-adjusted abnormal return	It is computed as the difference between the daily stock return and CSI 300 index market return
Next 1-month BHAR for individual Mil stock	The buy and hold abnormal return of Mil stock over next 1 month. The buy and hold abnormal return is computed as the buy-and-hold return of the stock minus same size portfolio's equal-weighted buy and hold return. The size portfolio is constructed according to market capitalization in previous month (all the stocks are divided into 10 quantiles).
Next 3-month BHAR for individual Mil stock	The buy and hold abnormal return of Mil stock over next 3 month. The buy and hold abnormal return is computed as the buy-and-hold return of the stock minus same size portfolio's equal-weighted buy and hold return. The size portfolio is constructed according to market capitalization in previous month (all the stocks are divided into 10 quantiles).
Next 1-month BHAR (Mil Portfolio)	For each account at month t, we take the next 1 month (i.e. month t+1) BHAR for the military portfolios held by each account, where the BHAR is the buy and hold investment return for the firm minus the buy and hold investment return for control portfolio. The control portfolio is constructed according to same market capitalization decile in previous month
Next 3-month BHAR (Mil Portfolio)	For each account at month t, we take the next 3 month (i.e. month t+1;t+2;t+3) BHAR for the military portfolios held by each account, where the BHAR is the buy and hold investment return for the firm minus the buy and hold investment return for control portfolio. The control portfolio is constructed according to same market capitalization decile in previous month.
Next 1 month weighted	For each account at month t, we take weighted average of next 1 month

average BHAR (Mil Portfolio)	(i.e. month t+1) BHAR for the military portfolios held by each account, with weight of dollar holding value of each military stock (holding shares*month end price), where the BHAR is the buy and hold investment return for the firm minus the buy and hold investment return for control portfolio. The control portfolio is constructed according to same market capitalization decile in previous month.
Next 3 month weighted average BHAR (Mil Portfolio)	For each account at month t, we take weighted average of next 3 month (i.e. month t+1;t+2;t+3) BHAR for the military portfolios held by each account, with weight of dollar holding value of each military stock (holding shares*month end price), where the BHAR is the buy and hold investment return for the firm minus the buy and hold investment return for control portfolio. The control portfolio is constructed according to same market capitalization decile in previous month.
First post-war generation	Dummy variable equals to 1 if age of the investor is between 40 and 65 (i.e. born between 1945-1970) and 0 otherwise;
High Media	A dummy variable that equals 1 if the total number of war memory related articles in the local media in the past 3 years is above the median of all the cities in a year and 0 otherwise.
Distance	It is the minimum distance between the city and 16 major iron ore mines (>5 million tons) found before the Second Sino-Japanese War. Our iron ore mine data is collected from Weng (1919).

Appendix B. The list of battle-suffered cities

This table shows detailed information for the Chinese historic battles this paper covers during the China-Japan War. *Historic Battles* is the name of the battle**.** *Japanese Mortality* is the officially reported mortality of Japanese side for the battle. Chinese Mortality is the officially reported mortality in a battle.[13]

Historic Battles	Japanese Mortality	Chinese Mortality	City	Province	Begin	End
Changheng	19380	17000	Changsha; Hengyang	Hunan	1944/5/27	1944/9/7
Changde	10000	60000	Changde	Hunan	1943/11/1	1944/1/6
Changsha1	20000	42000	Changsha	Hunan	1939/9/14	1939/10/15
Changsha2	7000	54000	Changsha	Hunan	1941/9/7	1941/10/9
Changsha3	56000	28612	Changsha	Hunan	1941/12/24	1942/1/16
Guangzhou	1923	2954	Guangzhou	Guangdong	1938/10/9	1938/10/29
Guiliu	13400	25665	Liuzhou; Guilin	Guangxi	1944/9/10	1944/12/1
Kunlunguan	5000	27014	Nanning	Guangxi	1939/12/18	1939/12/31
Lanfeng	6000	Unknown	Kaifeng	Henan	1938/5/21	1938/6/17
Longlin	13200	29803	Baoshan	Yunnan	1944/6/4	1944/7/9
Nankou	10000	29376	Beijing	Beijing	1937/8/7	1937/8/27
Nanchang	24000	52000	Nanchang	Jiangxi	1939/3/17	1939/5/9
Nanjing	12000	50000	Nanjing	Jiangsu	1937/12/5	1937/12/13
Pingjin	127	5000	Tianjin; Beijing	Tianjin; Beijing	1937/7/7	1937/7/30
Pingxinguan	1000	900	Xinzhou	Shanxi	1937/9/25	1937/9/25
Shanggao	15792	20533	Yichun	Jiangxi	1941/3/14	1941/4/9
Songhu	40000	333500	Shanghai	Shanghai	1937/8/13	1937/11/12
Songshan	1250	7763	Baoshan	Yunnan	1944/5/1	1944/9/30
Suizao	13000	20000	Suizhou; Zaoyang	Hubei	1939/5/1	1939/5/23
Taierzhuang	11974	20000	Zaozhuang	Shandong	1938/3/23	1938/4/7

[13] We only have the information on the mortality of soldiers.

Taiyuan	30000	100000	Taiyuan	Shanxi1	1937/7/1	1937/9/30
Tengchong	6100	18309	Baoshan	Yunnan	1944/5/11	1944/9/14
Wuhan	257000	400000	Wuhan	Hubei	1938/6/18	1938/10/25
Xinkou	20000	100000	Xinzhou	Shanxi1	1937/10/13	1937/11/2
Xuzhou	32000	100000	Xuzhou	Jiangsu	1938/1/1	1938/5/31
Zaoyi	7000	36983	Yichang; Zaoyang	Hubei	1940/5/1	1940/6/24
Zhongtiao shan	673	42000	Yuncheng; Jincheng; Linfen	Shanxi1	1941/5/7	1941/5/31

Appendix C.
Figure 2 Location of battle-suffered cities (i.e. treatment cities)