Culture vs. Bias:

Can Social Trust Mitigate the Disposition Effect?

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Abstract

We examine whether behavior bias related to mutual fund investment can be influenced by the social norms to which they are exposed. A higher level of social trust may elicit stronger investor reactions by increasing the *perceived* credibility of fund-reported performance. This effect enhances flow-performance sensitivity, which mitigates investors' disposition effect. Alternatively, societal trust may reduce concerns about expropriation, thereby weakening investors' need to react to poor performance. The resulting lower flow-performance sensitivity increases the disposition effect. Based on a proprietary dataset of complete account-level trading information for all investors in a large mutual fund family in China, we find compelling evidence 1) of a significant disposition effect among fund investors; 2) that a higher degree of social trust is associated with higher flow-performance sensitivity; and 3) that (high) trust-induced flows mitigate the disposition effect. Our results suggest that, in addition to cognitive biases, investor behavior is also strongly influenced by social norms.

Key words: Trust, The Disposition Effect, Mutual Funds

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Introduction

The disposition effect, i.e., the tendency to sell winning assets while holding onto losers (Shefrin and Statman, 1985) is regarded as one of the most prominent and robust "mistakes" that investors make (see Hirshleifer 2015 for a recent survey). While a vast body of literature examines and debates its causes and consequences (e.g., Barberis and Xiong 2009, 2012, Ben-David and Hirshleifer 2012, Henderson 2012, Li and Yang 2013, Frydman et al. 2014, and An 2016—to name just a few recent studies), the effect is typically interpreted as an individual-level cognitive phenomenon. By contrast, little attention has been paid to how this trading tendency is affected by the social interactions and social norms to which investors are exposed.[1] This gap deserves serious consideration, as potential analysis of how these social factors affect investor behavior could "provide greater insight into where heuristics come from (because they are far from entirely innate)" (Hirshleifer 2015).

Our paper aims to fill this gap by examining whether social trust affects the disposition effect among mutual fund investors. We are interested in social trust because it is one of the most influential elements of social norms. Indeed, as Nobel laureate Kenneth Arrow noted, "virtually every commercial transaction has within itself an element of trust" (Arrow, 1972), and social trust has been shown to mitigate contracting and informational incompleteness, thus affecting most major areas of the economy.[2] We focus on mutual fund investment because, as we will see shortly, we can use flow-performance sensitivity to identify the mechanism through which social trust affects the disposition effect.

Social trust can affect the disposition effect of mutual fund investment through two different channels. The first channel concerns the perceived creditability of information disclosed by funds. Since retail investors typically make investment decisions based on fund-reported performance, how creditable these performance numbers are from investors' perspective can significantly affect their decisions. Intuitively, perceived creditability can be thought as part of the subjective confidence interval that investors assign to fund reported information: investors should respond less to performance numbers in which they do not

[1] The only exception is Heimer (2016), which considers how participation in an investment-specific online social network affects the disposition effect among traders. More broadly related, Chui, Titman and Wei (2010) link individualism to overconfidence and self-attribution in explaining momentum. Grinblatt and Keloharju (2001) and Siegel, Licht and Schwartz (2011), and Eun, Wang, and Xiao (2015) also examine the influence of culture on investor trading behavior. But these papers do not focus on prominent behavioral biases such as the disposition effect. Karolyi (2016) provides a recent survey on the influence of culture in finance.

[2] Trust can mitigate contracting and informational incompleteness because it reduces the *subjective* probability of being cheated (e.g., Gambetta, 1988; Putnam, Leonardi, and Nanetti, 1993; Williamson, 1993; Fukuyama, 1995). Related to this economic consideration, social trust has been shown to affect, for example, economic growth (Knack and Keefer, 1997), international trade and investment (Guiso, Sapienza, and Zingales, 2009), financial development (Guiso, Sapienza, and Zingales, 2004, 2008), corporate transactions (Bottazzi, Rin, and Hellmann, 2011; Duarte, Siegel, and Young, 2012; Ahern, Daminelli, and Fracassi, 2012), firm size (La Porta et al., 1997; Bloom et al., 2009) and information dissemination (Pevzner, Xie, and Xin, 2015). Algan and Cahuc (2014) provide a survey.

have confidence. In this case, social trust can play a role because high-trust investors will perceive as more credible—and subsequently respond more to—fund-reported performance. This role is not dissimilar to the findings of Pevzner, Xie, and Xin (2015) that social trust induces investors to react more to unexpected earnings disclosed by firms because they perceive such information as more creditable.

New intuitions arise, however, when we link the above role to the well-documented effect in the mutual fund industry that investors respond to superior fund performance by investing more capital in funds and to poor performance by withdrawing capital from funds (e.g., Chevalier and Ellison 1997, Sirri and Tufano 1998, Spiegel and Zhang 2013). Adding social trust to this effect, we can see that high-trust investors should invest more (than low-trust investors) in funds with superior performance and withdraw more capital from poor performers due to their higher perceived creditability to such performance.[3] The most interesting observation is that social trust induces more return-chasing trading, which offsets the cognitive tendency to sell winners and hold onto losers. In this channel, therefore, social trust mitigates the common trading mistake of the disposition effect by inducing higher flow-performance sensitivity.

The second channel concerns perceived agency problems of funds. Since incomplete information is also known to exaggerate agency conflict between managers and investors (Jensen and Meckling, 1976; Myers and Majluf, 1984) and since superior performance is difficult for investors to identify *ex ante* (e.g., Carhart 1997), investors may instead be concerned with the agency problems of funds. In this case, investors withdraw capital upon receiving a signal of potential expropriation—i.e., poor performance. Since social trust is known to reduce concerns about expropriation by corporate insiders (e.g., Guiso, Sapienza, and Zingales, 2004, 2008; Georgarakos and Inderst, 2014), it can also lead mutual fund investors to worry less about agency issues, which reduces their need to react to negative signals (i.e., to sell poorly performing funds). In this case, a higher level of social trust will enhance the disposition effect by reducing the agency-related component of flow-performance sensitivity.

Both competing hypotheses share the intuition that the disposition effect is unlikely to be determined by investor-level cognitive heuristics alone—social norms may well exert some influence. Note that our goal is not to directly hypothesize how social norms affect cognitive heuristics. Rather, we propose that commonly *observed* behavior biases are likely to be influenced by social norms. Since such behavioral biases are often considered major sources of market inefficiency, a potential differentiation between their cognitive origins and social roots could have important normative and policy implications. Indeed, it may shift the focus from individual pathologies to common social and cultural issues, as emphasized by Hirshleifer (2015).

[3] If we consider a more drastic response to information to reflect less risk aversion, the effect of trust is also consistent with Gennaioli, Shleifer, and Vishny (2014a, b): trust in mutual funds reduces the investor's anxiety about taking a risk.

To empirically assess the influence of social norms, we exploit a new and unique proprietary dataset that contains complete account-level trading information for all investors in a large mutual fund family in China. The data include 2,621,450 accounts (much larger than the Odean 1998 dataset) invested in six equity funds of the fund family from 2002 to 2011. Investors come from all 31 regions (i.e., provinces) of Mainland China. This dataset is ideal for our tests for several reasons. First, unlike existing studies that explore the disposition effect among mutual fund investors via brokerage accounts (e.g., Odean, 1998, Chang, Solomon and Westerfield 2016), our data cover *all* of the distribution channels through which these funds offered by the family, including sales through brokerage firms and bank branches and through accounts directly opened online. That is, for each investor, we can construct an overall position with the fund family, regardless of the point of entry. Second, we have the *complete* trading history of the funds offered by the family for *all* investors. Our analysis is therefore free of data issues related to the unobserved trading activities of known investors (e.g., due to trading accounts missing from the data) or unobserved investors. Third, we are able to trace each investor's region of origin—through their National Identity Number—and thus identify the casual influence of culture therein. Fourth, the considerable regional heterogeneity in culture and social trust observed in China (e.g., World Values Survey 2001; Zhang and Ke, 2002) provides sufficient cross-sectional variation for our tests. Briefly, we draw inferences based on *all* trading activities of *all* investors from *all* regions in China that trade the funds offered by the family, thereby avoiding investor- or trading activity–related data issues.

To better link the disposition effect to regional culture, we aggregate investor accounts at the regional level. In each month, we identify for each investor whether a position in a particular fund implies a capital gain or loss based on the entire trading history of that investor. Due to different trading histories, the same price and fund may imply capital gains for some investors but losses for others. We then aggregate these accounts at the regional level for each distribution channel. In the spirit of Ben-David and Hirshleifer (2012), we compute the probability of selling winners ("PSW") by investors in the same region as the fraction of investors in the region who sell their mutual funds at capital gains. Analogously, the probability of selling losers ("PSL") is the fraction of investors selling at capital losses. The regional disposition effect is then defined as the difference between the PSW and the PSL.

In our sample, the PSW in a typical month is 1.68% at the regional level, which is much higher than the PSL (1.18%), confirming that investors in our sample exhibit a strong disposition effect (approximately 0.49%). Interestingly, this magnitude is very close to Ben-David and Hirshleifer's (2012) finding for the disposition effect among short-term sales within 20 days of purchase (also 0.49%). Mutual fund investment in our sample, in this regard, is not that different from stock trading in their sample in terms of the disposition effect. Unreported tests further show that the disposition effect is related to more trading losses, which is consistent with the common interpretation of the effect as a mistake.

We then analyze the link between the disposition effect and social trust in two steps to test the two competing hypotheses. In the first step, we assess the influence of social trust (based on a survey by Zhang and Ke, 2002; hereafter, ZK) on mutual fund flows. We find that a high degree of social trust can significantly increase flow-performance sensitivity. Indeed, a one-standard-deviation increase in social trust is associated with a 59% increase in flow-performance sensitivity (scaled by the level of flow-performance sensitivity; we will discuss the details in later sections). This observation suggests that social trust enhances mutual fund investors' responses to information, which is generally consistent with the finding of Pevzner, Xie, and Xin (2015) that trust increases (stock market) investors' responses to earnings information.

The second step of the analysis explores the influence of social trust on the disposition effect channeled through fund flows. Specifically, we examine the relationship between the out-of-sample estimated disposition effect and the additional part of fund flows that is induced by social trust, which we label *trust-induced flows*. *Trust-induced flows* are estimated over several rolling windows as well as over the entire sample period. We find compelling evidence that the two are negatively related. When we link the disposition effect in a month to *trust-induced flows* estimated over the previous 12-month rolling window, for instance, we find that a one-standard-deviation increase in *trust-induced flows* is associated with a 27.6% decrease in the disposition effect. As a placebo test, we also consider fund flows that are not induced by trust—which we label *other flows*. We find that *other flows* are unrelated to the disposition effect. These results lend support to the hypothesis that social trust mitigates the disposition effect.

The findings of these two steps can be graphically illustrated. In Figure 1, we plot the relationship between regional trust and the average flow-performance sensitivity of aggregated accounts in the same region estimated over the entire sample period. In Figure 2, we plot the relationship between the average *trust-induced flows* of a region and its average disposition effect (both are averaged over the entire sample period). We observe a positive relationship in Figure 1 and a negative relationship in Figure 2. These patterns clearly illustrate that social trust mitigates the disposition effect through its influence on fund flows.

After obtaining these baseline results, we further examine how trust affects the two elements of the disposition effect, the PSW and the PSL. We find that *trust-induced flows* significantly reduce the former but increase the latter. Hence, social trust mitigates the disposition effect by inducing investors to buy more winners and sell more losers. Even more importantly in terms of distinguishing the two hypotheses, we find that contrary to the expropriation hypothesis, social trust reduces the tendency to hold onto losers. By contrast, *other flows* affect PSW and PSL similarly, thereby offsetting their influence on the disposition effect.

One potential concern is that the disposition effect and trust may be spuriously correlated due to unobserved region characteristics or reverse causality. This concern is likely to be inconsequential because we explicitly control for region fixed effects in our out-of-sample tests and because any characteristic other than trust should not only affect *trust-induced flows* but also *other flows* in the placebo test (e.g., in terms of PSW and PSL). Nonetheless, we conduct an endogeneity test related to the diffusion of culture in a society. A few recent studies (Guiso, Sapienza, and Zingales, 2006, Fisman and Miguel, 2007, DeBacker, Heim, and Tran, 2015, and Liu, 2016) show that immigrants can bring social beliefs from their countries of origin to their destination countries. Building on this intuition, we hypothesize that mutual fund investors can also be influenced by their regions of origin, allowing the social trust therein to influence their later trading habits.

To test this intuition, we use the National Identity Numbers of investors to trace their region of birth (i.e., their region of origin) and apply our previous tests to investors whose trading locations differ from their regions of origin (i.e., migrants). We then examine the influence of the social trust in the region of origin on the disposition effect. This test nets out the potential influence of any unobserved trading region characteristics and alleviates concerns about reverse causality (as it is difficult, if not impossible, for the trading habits of a few investors in Beijing to affect the social trust of their hometowns).

We consider both the subsample of migrant investors whose accounts are located in the top three host regions in China (i.e., Guangdong, Jiangsu, and Beijing in our sample) and the entire sample of migrant investors. In both subsamples, we find that trust in the region of origin significantly influences the magnitude of the disposition effect among migrant investors. Interestingly, we also find that home-region trust has a stronger influence on the loss side; hence, the two sides of the disposition effect may not be equally affected by their exposure to social norms. This finding may provide some heuristics for future research. Overall, these results provide a causal interpretation of our previous findings.

Our results are robust to the use of an alternative survey (i.e., the World Values Survey 2001; hereafter, WVS) as well as to the use of donations after the Great Sichuan Earthquake in 2008 as the measure of social trust. Moreover, our results hold regardless of the distribution channel used by the investor to access the fund. Finally, we find that the influence of social trust on the disposition effect is more prominent in retail accounts than in institutional accounts.

To the best of our knowledge, we are the first to document that social trust may significantly influence the behavior of individual investors. The closest paper to ours is Heimer (2016), which explores how online social networks affect the disposition effect. Our study differs by starting from social trust, one of the most fundamental cultural elements known to affect our economy (Arrow, 1972; Gambetta, 1988; Putnam, Leonardi, and Nanetti, 1993; Williamson, 1993; Fukuyama, 1995; Knack and Keefer, 1997; La Porta et al., 1997; Guiso, Sapienza, and Zingales 2004, 2008, 2009; Bloom et al., 2009; Bottazzi, Da Rin, and Hellmann, 2011; Georgarakos and Inderst 2011; Ahern, Daminelli, and Fracassi, 2014; Duarte, Siegel, and Young, 2012; Sapienza and Zingales, 2012; Gennaioli, Shleifer, and Vishny, 2014a, b; Pevzner, Xie, and Xin, 2014). We contribute to this fast-growing literature by demonstrating that the influence of culture can be extended to fields that are traditionally part of the behavioral finance literature.

By doing so, we extend the literature on the disposition effect (Shefrin & Statman 1985, Barberis & Xiong 2009, 2012, Ben-David & Hirshleifer 2012, Henderson 2012, Li & Yang 2013, Frydman et al. 2014, An 2016, Chang, Solomon and Westerfield 2016; Hirshleifer 2015 provides a recent survey). Specifically, our results indicate that, in addition to cognitive heuristics, social norms also play an important role in affecting the trading behavior of individual investors. Note that our results do not imply that social norms may affect cognitive heuristics. Rather, both cognitive and social forces are important in that any *observed* behavior of individual investors is likely to have already incorporated the influences of the two. In this regard, our finding of a disposition effect among mutual fund investors in China should not be taken as a critique of Chang, Solomon and Westerfield (2016), who find a reverse disposition effect among U.S. mutual fund investors. To the contrary, the differences between these two groups of investors highlight the potential importance of country-level characteristics, such as social norms, in shaping investor behavior, echoing Hirshleifer's (2015) call to "move beyond behavioral finance to social science".[4]

Finally, our study extends an emerging body of literature that examines the role of trust in the mutual fund industry (e.g., Gennaioli, Shleifer, and Vishny, 2014a, b; Massa, Wang, Zhang, and Zhang 2016). Our major contribution here is to clarify how trust affects fund flows and managerial incentives. In particular, it may be tempting to think that trust provides more room for managerial expropriation. Our results indicate the opposite, which is consistent with the finding of Massa, Wang, Zhang, and Zhang (2016) that managers' behavior is typically trustworthy in a high-trust culture. This clarification also extends our existing understanding of the formation and impact of fund flows (e.g., Chevalier and Ellison 1997, Sirri and Tufano 1998, Spiegel and Zhang 2013).

The remainder of the paper is organized as follows. Section II presents our variables and summary statistics. Section III reports the relationship between trust and the disposition effect. Section IV explores the endogeneity test on migrant investors. Section V discusses additional robustness checks. Finally, Section VI concludes.

II. Data and Variable Construction

[4] In spirit of Fukuyama (1995), for instance, the difference may well reflect the existence of different equilibria in the presence of high or low trust.

We now describe the sources of our data and the construction of our main variables.

A. Sample and Data Sources

Our data come from a confidential mutual fund family in China. The mutual fund family is located in Shanghai. It has a 3% market share in China, both in terms of the number of mutual funds offered and in terms of total net assets (TNA) under management, with investors from all 31 regions in Mainland China. The fund family allows investors to open investment accounts either directly online or indirectly through brokerage firms or bank branches. It is common practice for Chinese fund families to use all three distribution channels. Each investor is allowed to open only one account through these channels, which is registered under his or her National Identity Number (at any given time, each citizen in China has a unique National Identity Number). After opening the account, investors can buy shares of any fund offered by this family and/or redeem their existing shares. The investment rules on the operations side of mutual fund investment are identical to those in the U.S.

For each account, the database allows us to retrieve information about the a) investor profile, b) trading history, and c) dividend distributions. The investor profile contains the personal information about an investor, including his or her unique National Identity Number, date of birth, gender, postcode and distribution channel. The trading file provides, for each transaction, the name of the mutual fund involved, the total number of shares purchased or redeemed, the total value of the purchase or redemption, the total transaction fees related to these transactions, and the total number of shares after the transaction. Finally, the dividend file provides information regarding the type and total amount of dividends distributed to each investor based on his/her share holdings in the specific mutual fund. Detailed information about the data is provided in Appendix B.

For each investor, the unique National Identity Number allows us to trace the region (i.e., the province) of birth, whereas the postcode allows us to verify the region of residence. Moreover, from account-level trading and dividend information, we can trace the entire trading history of each account, as well as its gains and losses. Occasionally, other types of transactions may be recorded, including swaps between different funds within the mutual fund family, the establishment of automatic purchase plans, and switches between dividend choices. We manually review all the records that may be treated as a buy or sell and transform them into purchase/redemption quantity and price data. Our results are not affected when we exclude these records.

To make our results easily comparable with the literature on the disposition effect (e.g., Chang, Solomon and Westerfield, 2016) and flow-performance sensitivity (e.g., Chevalier and Ellison 1997, Sirri and Tufano 1998, Spiegel and Zhang 2013), we focus on the open-end equity funds offered by the family.

Compared to the existing brokerage dataset of Odean (1998), which has also been used to examine the disposition effect among mutual fund investors (e.g., Chang, Solomon and Westerfield, 2016), our sample is more complete in the sense that it includes *all* trading activities of *all* investors from *all* regions in China that trade these funds. An additional benefit of our data is that investors do not pay taxes on capital gain or dividend payouts in China. This feature eliminates the confounding effects of tax-motivated selling activities. In addition to these considerations, we require a fund operations history that is longer than five years so that we can have a long period over which to examine the disposition effect. Our final sample includes 2,621,450 investment accounts trading six equity funds from 2002 to 2011, which is much larger than the sample of 128,829 accounts of mutual fund investors reported in Chang, Solomon and Westerfield (2016) based on the Odean (1998) dataset.

Pricing information and equity mutual fund characteristics come from two major sources: China Stock Market and Accounting Research (CSMAR), which is available from the Wharton Research Data Services (WRDS), and the Wind Financial Database (WIND), another leading integrated service provider of financial data, information, and software. From these two databases, we retrieve daily prices (i.e., the net asset value or NAV), returns, and TNA for the six equity funds, as well as characteristics such as fund fees and benchmarks. We crosscheck the two databases to ensure the accuracy of all the information. We check the quality of account-level data by aggregating the NAV of all accounts at the fund level. We find that the aggregate asset value derived from individual accounts matches the TNA reported by CSMAR and WIND, confirming that we have complete information about all investors that trade these funds.

B. Main Variables

We first describe our proxies for social trust and then describe the variables related to the disposition effect. To provide a measure of social trust that may affect the way investors respond to information or expropriation, we follow Hong et al. (2015) and use the logarithm of the trust scores derived from the ZK survey. This survey asks corporate senior managers to rank regions on the basis of how their general trust in corporations there and then computes trust scores to describe the trustworthiness of each region from the responses of all survey participants. A higher trust score is assigned to a region when a higher fraction of participants reports that they can, in general, trust companies therein. Compared to the other popular survey – e.g., the WVS that we will discuss shortly – the coverage of the ZK survey is more complete and includes all 31 Chinese provinces. More importantly, the ZK survey has the advantage of providing a proxy for social trust that is directly rooted in the business environment of a region. Since trust and trustworthiness are largely reciprocal (see, e.g., Algan and Cahuc 2014 for a survey and theoretical treatment; Berg, Dickhaut, and McCabe 1995 and Baran, Sapienza, and Zingales 2010 for laboratory experiments; and Massa, Wang, Zhang, and Zhang 2016 for evidence in the global mutual fund industry), the ZK survey provides a nice business-oriented measure of social trust that we expect to affect the investment behavior of investors. We thus use this measure as our main proxy for social trust (*Trust_ZK*). Any potential discrepancy between trust and trustworthiness only works against us in finding anything.

To complement the above proxy which focuses more on trustworthiness, we also construct an alternative proxy of social trust that considers whether people in a region trust others. This proxy is based on the World Value Survey (WVS), which asks respondents whether most people can be trusted (see, e.g., Guiso, Sapienza, and Zingales, 2008 and Ahern et al., 2014 for more details). The WVS survey focuses on country-level statistics and is thus widely used for cross-country studies. The survey wave conducted in 2001 also provides regional results for China, although the coverage is not as complete (seven regions, for instance, are not covered). Nonetheless, the WVS survey provides a reasonable alternative measure of social trust that we can use to check the robustness of our first measure. Relying on this survey, we define social trust as the fraction of participants who think that most people can be trusted in each region (*Trust_WVS*).

We also consider a third proxy for trust that is based on the donations that people made after the 2008 Sichuan earthquake – arguably the most severe earthquake to affect China in the last two decades. This variable captures an important element of social trust because donors face similar issues when deciding to donate money to help the victims of a natural disaster to those faced by investors when they make investment decisions. Indeed, donors have incomplete information about donation-related operations and worry about potential expropriation. Therefore, the level of donations reveals the degree of social trust among the people in a region when they face such issues. We define a proxy for trust (*Donation*), which is computed as the money and materials that people from a region donated after the 2008 Sichuan earthquake, scaled by either the population or gross domestic product (GDP) of the region.

To identify the effect of trust, it is important to control for potentially confounding effects. We therefore consider three sets of region-level variables that could also affect mutual fund investors. The first set is related to the economic growth of the region. The variables include GDP in billions (*Log_GDP*), inflation rate (*Log_inflation*), dollar amounts of imports and exports (*Log_import* and *Log_export,* respectively), unemployment rate (*unemploymentrate*), total population in the region (*Log_pop*), average disposable residence income (*Log_residence_income*) and total bank savings in the providence of residence (*Log_bank_saving*). When appropriate, we use the logarithm of the raw values to mitigate the skewness of the distribution. The second set of variables captures the influence of the regional government – a major factor in China's economy. These variables include government expenditure (*Log_gov_exp*), the number of state-owned firms (*Log_num_state_firms*), the number of private firms (*Log_num_private_firms*), the number of employees working for public firms (*Log_num_employ_public*), and the number of employees working for private firms

(*Log_num_employ_private*). The third set of variables controls for other elements of culture, including linguistic diversity (*LD*), the number of languages spoken in that province, the fraction of terrain that is hilly (*Hill*) in each province, the number of ethnicities in the region (*Ethnicity*), the number of religions in the region (*Religion*), and the number of stocks headquartered in each region divided by number of all stocks in the country (*List_localfirm*). The first two sets of variables come from the National Bureau of Statistics, while the construction of the last set of variables follows Hong et al. (2015).

We now describe the variables related to mutual fund investment. First, to better link investor behavior to regional culture, we aggregate investors' trading activities for each equity mutual fund at the regional level. Since different distribution channels may imply different trading tendencies—for instance, investors using online accounts may trade more aggressively—we also consider the distribution channel that investors use. Based on these considerations, we aggregate all the investment/redemption activities in the same region, distribution channel and fund into a *region-channel-fund* account. When there is no confusion, we refer to such accounts as *regional accounts*. Intuitively, each regional account describes the trading activities of a representative regional investor who buys and sells shares of a particular fund via a specific distribution channel.

All the investment variables are then defined for these regional accounts. We first define the ratio of capital flowing into an account (denoted $Inflow$) as the value of new purchases of a fund scaled by the lagged value of the existing shares (i.e., TNA) of the account and the ratio of capital flowing out of an account (denoted $Outflow$) as the value of redeemed shares scaled by the lagged TNA of the account. The net flow of an account, denoted $Netflow$, is then defined as the difference between the two:

$$Inflow_{g,i,f,t} = \frac{Total\ Value\ of\ Purchases_{g,i,f,t}}{Total\ Net\ Assets_{g,i,f,t-1}},$$

$$Outflow_{g,i,f,t} = \frac{Total\ value\ of\ Redemptions_{g,i,f,t}}{Total\ Net\ Assets_{g,i,f,t-1}},$$

$$Netflow_{g,i,f,t} = Inflow_{g,i,f,t} - Outflow_{g,i,f,t},$$

where $Inflow_{g,i,f,t}$, $Outflow_{g,i,f,t}$, and $Netflow_{g,i,f,t}$ refer to the inflow, outflow, and net flow ratios of the aggregate account of region g, channel i, and fund f in period t. The definition of fund flow is consistent with the mutual fund literature, except that the literature does not usually directly observe separate inflows and outflows of funds in the U.S. Based on these variables, we construct monthly flow ratios for each of the regional accounts.

We then move on to construct variables that describe the disposition effect for these regional accounts. Since the disposition effect is essentially the difference between the probability of selling winners (PSW) and that of selling losers (PSL), we start by constructing these probabilities for our regional accounts. To do so, we use the original data for each investor and compute the capital gains and losses that each investor could realize by trading a particular fund on a particular day.

Specifically, for each investor-fund-day observation, we follow the literature (e.g., Odean, 1998; Frazzini, 2006; Ben-David and Hirshleifer, 2012) and calculate the purchasing cost of the inventory of each investor derived from his or her entire trading history in the fund.[5] We then compare this reference price with the market price of the fund reported by CSMAR. We flag an investor-fund-day observation as a *capital gain* if the current price is strictly above the reference price based on the investor's entire trading history. Similarly, an investor-fund-day is flagged as a *capital loss* if the current price is strictly below the reference price.

Then, for each aggregate regional account, we use the proportion of individual investors therein who sell shares of the fund conditional on capital gains to proxy for the probability of selling winners (PSW). Likewise, we use the proportion of investors who sell shares of the fund conditional on capital losses to proxy for the PSL. The final proxy for the disposition is then defined as follows:

$$Disposition_{g,i,f,t} = PSW_{g,i,f,t} - PSL_{g,i,f,t},$$

where $Disposition_{g,i,f,t}$ is the proxy for the disposition effect for the aggregate account of region g, channel i, and fund f in period t.

We also control for fund-level variables that can be correlated with fund performance or trading. *Ret* refers to the benchmark-adjusted return, which is calculated as the difference between the after-fee return of a fund in a month and its benchmark return.

Next, different distribution channels may result in varying flow-performance sensitivity. For instance, investors could value their relationships with banks the most and therefore be reluctant to withdraw capital even when a fund performs poorly. Accordingly, we define the *Channel* variable to capture this effect. The variable takes the values 0, 1, and 2 for the bank branch, brokerage firm, and direct online account distribution channels, respectively. *Log(TNA)* is the logarithm of the mutual fund's total net assets in millions of RMB. *Mfee* is the percentage of the management fee as a share of fund TNA. *Fundage* is the number of days of operation since a fund's inception.

C. Summary Statistics

Table 1 presents summary statistics for our sample. Panel A tabulates the mean, median, standard deviation, and quantile distribution of the variables that describe trading behavior for aggregate regional accounts. Panels B, C, and D report similar statistics for the fund-level control variables, additional culture variables, and region-level control variables, respectively. We can see that the mean (median)

[5] We follow Frazzini (2006) and assume that investors use a cost-based mental accounting method (FIFO-first in, first out) to associate a quantity of shares in their trading account to the corresponding reference price.

value of *Inflow* is 0.054 (0.003)—or 5.4% (0.3%)—and that of *Outflow* is 0.066 (0.019). Hence, the net flow is negative in our sample, with a mean (median) value -0.012 (-0.006). The observation that outflows outweigh inflows suggests that our sample includes sufficient selling behavior to measure the disposition effect.

Next, we observe that the PSW in a typical month is 1.68% for aggregate regional accounts, which is much higher than the PSL (1.18%). Hence, investors, on average, exhibit a strong disposition effect in our sample. Indeed, the average intensity of the disposition effect (0.49%) is very close to the disposition effect of active, short-run trading (0.49% for sales made within 20 days of purchase) reported in Ben-David and Hirshleifer (2012). Although we examine two very different samples of investors, this similar finding suggests that Chinese and U.S. investors share common factors in terms of the disposition effect.

Panel E reports the correlation matrix of the main variables (the Internet Appendix provides a correlation matrix for all the variables). We find that societal trust is negatively correlated with the disposition effect. This observation, though preliminary, lends some support to the view that social trust might affect investor behavior. Moreover, consistent with the hypothesis that trust can mitigate the disposition effect through its influence on fund flows, we observe that *trust-induced flows*—which we will define shortly—is negatively correlated with the disposition effect. Of course, these numbers could be spuriously related to many fund or regional characteristics. Therefore, in the next section, we perform formal multivariate tests.

III. Trust and the Disposition Effect: Baseline Results

In this section, we investigate the general relationship between trust and the disposition effect in two steps. We start by analyzing the flow-performance sensitivity of mutual fund investment and then investigate how trust-inducted flows affect the disposition effect.

A. Trust and Flow-performance Sensitivity

We first investigate whether and how trust affects the flow-performance sensitivity of fund investment. To achieve this goal, we interact social trust with fund performance in traditional flow-performance tests of fund investment as follows:

$$Netflow_{g,i,f,t} = \alpha + \beta \times Ret_{f,t-1} + \delta \times Trust_g + \gamma \times Trust_g \times Ret_{f,t-1} + C \times M_{g,i,f,t-1} + \varepsilon_{g,i,f,t}, (1)$$

where $Netflow_{g,i,f,t}$ is the net flow ratio of the aggregate account of region g, channel i, and fund f in period t; $Ret_{f,t-1}$, is the excess return of fund f (in access of the market) in the previous month; $Trust_g$ is the logarithm of the trust index in region g; and Ch_i refers to the distribution channel i for fund f at month *t-1*. Here, $M_{g,i,f,t-1}$ is a vector of fund-level control variables, including Ch_i, which captures the influences of the distribution channels; *Lag_netflow*, the aggregate mutual fund flow in month *t-1*; *Log(TNA),* the logarithm of the total net assets of fund f at month *t-1*; and *Fundage*, the logarithm of the number of operating days since fund inception. We estimate a panel specification with fund, time, and region fixed effects, and their standard errors are clustered at the region level. Our results are robust to alternative specifications and different sets of control variables.

We report the results in Table 2. Model (1) confirms that investment flows are in general positively related to past performance, as reported in the mutual fund literature (e.g., Chevalier and Ellison 1997, Sirri and Tufano 1998, Spiegel and Zhang 2013). From this perspective, mutual fund investors in China are not different from those in the U.S. It is worth noting that the existing literature focuses on a cross-section of funds in making inferences about flow-performance sensitivity, while we use a cross-section of investors to understand how different investors respond to (the same piece of) information. In other words, existing studies typically ask whether a particular fund receives more capital than another fund when it outperforms the other fund, whereas we consider whether a particular group of investors has a stronger response to the same performance indicators due to differences in social norms between groups.

Models (2) and (3) introduce trust and the interaction between trust and returns, respectively. We observe that social trust is positively related to flows, but the influence is not economically large. We focus on the interaction term in Model (3). The coefficient is significant and positive (0.091, with a t-statistic of 3.5), suggesting that social trust enhances flow-performance sensitivity. A one-standard-deviation increase in social trust, which is 1.09 in our sample, implies an increase in flow-performance sensitivity equal to 0.0981 (i.e., $0.091 \times 1.09 = 0.0981$). If we compare this number to the level of flow-performance sensitivity, which is 0.163 in the same regression model, a one-standard-deviation increase in social trust implies a 60.9% relative increase in flow-performance sensitivity.[6] The result is robust to further controls for the potential effects of the distribution channels in Model (4), region fixed effects in Model (5), and additional regional variables (in addition to region fixed effects) in Model (6). Overall, these results suggest that social trust enhances flow-performance sensitivity.

B. The Baseline Regression between *Trust-induced Flows* and the Disposition Effect

Although the impact of trust on flow-performance sensitivity shed some light on the role of trust in the mutual fund industry, we need to more formally link the influence of trust on flows to the disposition

[6] Mathematically, the economic magnitude of the marginal impact of trust is estimated as $\gamma \times \sigma_{Trust}/\beta = 0.091 \times 1.09/0.163 = 60.9\%$, where γ and β are regression coefficients as in Equation (1), and σ_{Trust} is the standard deviation of social trust.

effect. We therefore construct trust-induced flows based on the previous results and examine how these flows affect out-of-sample estimates of the disposition effect.

Specifically, for a given month t, we can use the 12-month rolling window prior to that month to estimate the coefficients in Equation (1). We then define *trust-induced flows* as $\widehat{Flow}^{Trust}_{g,i,f,t|t-1} = \hat{\gamma} \times Trust_g \times Ret_{f,t-1}$, where $\hat{\gamma}$ is the estimated coefficient of the interaction term in the rolling window from $t-12$ to $t-1$. This interaction term separates the specific information impact of social trust from the general region fixed effects, which allows us to take advantage of the time variation in fund performance (as social trust variables are static) to construct time-varying independent variables that are suitable for out-of-sample tests. The difference between realized flows in the month and *trust-induced flows* is then defined as *other flows*, denoted $\widehat{Flow}^{Other}_{g,i,f,t}$.

We then regress the out-of-sample estimated disposition effect on *trust-induced flows* in the following panel specification:

$$Disposition_{g,i,f,t} = a + b \times \widehat{Flow}^{Trust}_{g,i,f,t|t-1} + c \times \widehat{Flow}^{Other}_{g,i,f,t} + d \times M_{g,i,f,t} + \varepsilon_{g,i,f,t}, \quad (2)$$

where $Disposition_{g,i,f,t}$ refers to the disposition effect of the aggregate account of region g, channel i, and fund f in period t, $\widehat{Flow}^{Trust}_{g,i,f,t|t-1}$ and $\widehat{Flow}^{Other}_{g,i,f,t}$ are *trust-induced flows* and *other flows*, respectively, and $M_{g,i,f,t}$ is a vector of control variables for each region. We further control for time, fund, and region fixed effects, and we cluster the standard errors at the region level.

Note that *trust-induced flows* estimated for period t ($\widehat{Flow}^{Trust}_{g,i,f,t|t-1}$) are estimated strictly on the basis of $t-1$ information. Hence, the disposition effect is estimated out-of-sample with respect to *trust-induced flows*. In contrast, the *other flows* variable for period t (i.e., $\widehat{Flow}^{Other}_{g,i,f,t}$) may involve period t information. Although this definition implies that the disposition effect is not out-of-sample with respect to *other flows* in our placebo tests, it only increases the power of *other flows* and works against us in finding significant results for *trust-induced flows*. Furthermore, when *other flows* is not included, Equation (2) is strictly out-of-sample. Later tests will show that our results are robust regardless of whether $\widehat{Flow}^{Other}_{g,i,f,t}$ is included. The Internet Appendix further shows that our results are robust to the use of alternative ways of estimating *trust-induced flows* and *other flows.*

We tabulate the results of Equation (2) in Table 3. In Models (1) to (2), Models (3) to (4) and Models (5) to (6), trust-induced flows are estimated over a 12-month rolling window, a 6-month rolling window, and the entire sample, respectively. We can see that *trust-induced flows* are, in general, negatively associated with the disposition effect. Importantly, when we introduce *other flows* into the same test in

Models (2), (4) and (6), we find that *other flows* are unrelated to the disposition effect. This placebo test lends strong support to the hypothesis that social trust mitigates the disposition effect.

The magnitude of the influence can be estimated as follows. In Model (2), for instance, a one-standard-deviation increase in *trust-induced flows* is associated with a 5% decrease in the magnitude of the disposition effect. Compared to the average disposition effect of 0.49% that investors exhibit in the sample, this one-standard-deviation impact represents a 27.6% decrease in the disposition effect in relative terms.[7] The economic significance computed similarly for *trust-induced flows* over 6-month rolling windows and the entire sample is 21.3% and 25%, respectively.[8] These numbers suggest that the influence of trust on the disposition effect is not only statistically significant but also economically sizable.

C. A More Detailed Look at the PSW and the PSL

So far, our baseline results show that *trust-induced flows* significantly affect the disposition effect. Since the disposition effect involves two legs, namely, the PSW and the PSL (e.g., Ben-David and Hirshleifer 2012), it is important to understand which leg is more affected. This additional test may provide more insight into explanations that rely on loss aversion (e.g., Kahneman and Tversky 1979).

To achieve this goal, we replace the overall disposition effect in our previous table with the separate PSW and the PSL values. The results are tabulated in Table 5 in which *trust-induced flows* are again estimated using various rolling windows (Models (1) to (4) use 12-month windows; Models (6) to (8), 6-month windows) or over the entire sample period (Models (9) to (12)). We find that *trust-induced flows* significantly reduce the PSW but increase the PSL. This result is consistent with the directions of trading depicted in the mitigation hypothesis, which holds that high trust induces investors to buy more winners

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[7]The mean and standard deviation of the disposition effect are 0.0049 and 0.0274, respectively, in Table 1. The economic magnitude for the regression of $y = \beta \times x$ is computed as $\beta \times \sigma_x / |\bar{y}|$, where y and x are the dependent and independent variables, respectively, β is the regression coefficient, σ_x is the standard deviation of x, and $\bar{y}$ is the mean of y. For instance, the standard deviation of *trust-induced flows* is 0.018 in our sample, and the regression coefficient in Model (2) is -0.075. From these numbers, we compute the economic magnitude as $-0.075 \times 0.018/0.049 = 27.6\%$, which implies a 27.6% reduction in the disposition effect. Note that we scale the impact by the mean value of the disposition effect. Alternatively, we can use the standard deviation of the dependent variable to scale the economic magnitude. In this case, a one-standard-deviation increase in *trust-induced flows* is related to a 5% decrease in the disposition effect. However, this interpretation may underestimate the influence of social trust because we wish to understand how social factors affect the average disposition effect. To see the intuition, consider the case in which a hypothetical social factor reduces the average effect of disposition to zero. In this case, the social factor significantly influences investors' trading tendency even though cognitive biases may nonetheless introduce huge variations in the cross-section. Moreover, scaling by the standard deviation may underestimate the influence of social trust because of the skewed distribution of the disposition effect. Hence, we mainly use the former scaling method, but we also report the latter scaling when applicable.

[8] These one-standard-deviation influences are equivalent to 5%, 3.87%, and 4.53% of the standard deviation of the disposition in the three scenarios, respectively.

(and hence reduces the probability of selling them) and redeem more losers (and hence increases the PSL).

These results are both statistically and economically significant. In Models (2), (6) and (10), a one-standard-deviation increase in *trust-induced flows* of approximately 0.018 is associated with reductions of 6.54%, 5.14%, and 3.21%, respectively, in the likelihood of selling winners scaled by the average PSW. Meanwhile, Models (4), (8) and (12) show that the same one-standard-deviation increase in *trust-induced flows* is associated with increases of 3%, 2.29%, 6.86%, respectively, in the PSL.[9]

By contrast, *other flows* affect PSW and PSL similarly. An economic interpretation of this similarity is that absent the influence of trust, a negative liquidity shock would lead investors to sell winners and losers with equal probabilities. Similar changes in both directions offset their effects, leaving the disposition effect unaffected. This placebo test is important, as it suggests that *trust-induced flows* are likely to capture something fundamental to the disposition effect and distinct from other potentially confounding effects.

To sum up, we conclude that social trust mitigates the disposition effect by inducing investors to both buy more winners and sell more losers. Contrary to the expropriation hypothesis, social trust reduces the tendency to hold onto losers, suggesting that social norms may also affect the trading influence of loss aversion.

IV. Endogeneity Test based on Migrating Investors

One concern related to our previous results is that the disposition effect and trust may be spuriously correlated due to unobserved regional characteristics or reverse causality. The designs of our previous tests aim to mitigate this concern; we conducted out-of-sample tests that explicitly controlled region fixed effects and used flows unrelated to trust as a placebo test. Indeed, it is unlikely that characteristics other than trust will affect *trust-induced flows* without affecting *other flows* in the placebo test.

In this section, we nonetheless use the identification number of each investor to trace his or her region of birth and apply our previous tests to migrant investors, those whose trading locations differ from their region of birth. This test is similar to those in studies that examine immigrant transfer of social beliefs from their countries of origin – in our case, regions of birth – to new countries (Guiso, Sapienza, and Zingales, 2006, Fisman and Miguel, 2007, DeBacker, Heim, and Tran, 2015, and Liu, 2016) and thus

[9] For instance, in Model (2), the regression coefficient of 12-month rolling window on the PSW is negative 0.061. A one-standard-deviation increase in *trust-induced flows*, which is 0.018 in the sample, compared to the mean of the probability of selling winners of 0.0168, implies a change of $-0.061 \times \frac{0.018}{0.0168} = -6.54\%$ in the disposition effect.

offer a causal interpretation of the potential influence of culture.

A. Migrant Investors in Our Sample

Internal migration in China is extensive. According to the Fifth National Population Census of the People's Republic of China (2000), 42.4 million people live outside of their home provinces, including but not limited to migrant workers and students, which is approximately 4% of the population. The largest migrant populations are in Guangdong, Shanghai, and Beijing, which jointly contribute more than one-half of the total migrant population.[10]

Our sample also contains migrant investors whose trading locations differ from their regions of birth. Since each investor can only register one account with the fund family, in most cases, the trading location is the residence of the investor. National Identity Numbers, on the other hand, allow us to trace the region of birth of each investor. There are 51,626 accounts associated with migrant investors, representing approximately 2% of the total number of accounts in our sample. The fraction of migrant investors in our sample is smaller than that of the entire population. This difference is reasonable because a large portion of the migrant population is employed in relatively low-skill manufacturing. Mutual fund investors, by contrast, are relatively wealthier and less mobile.

Consistent with the general census, the top host region for migrant investors in our sample is Guangdong (5,449 accounts), followed by Jiangsu (3,907 accounts) and Beijing (3,382 accounts). Interestingly, Shanghai-based migrant investors are outnumbered by the top three regions even though the fund family is located in Shanghai. To ensure that our results are robust, we focus on two subsamples of migrant investors in our tests: 1) migrant investors who are located in the top three regions and 2) all migrant investors regardless of their trading location. The focus on the subsample of investors in the top three trading regions minimizes the potential influence of the host regions, whereas the whole-sample test allows us to assess the overall robustness of our conclusion. Regardless of the sample used, we always include region fixed effects to control for the trading location.

B. Subsample Analysis of Migrant Investors

We now apply the baseline specification of Equation (2) to trust and the disposition effect among migrant investors. We use National Identity Numbers to trace the investors' regions of birth, which we treat as the regions of origin in terms of social trust. Then, we aggregate the trading behavior of the investors that migrated from each region of origin following the same process described in Section II. This allows us to construct variables describing both the flow information and the disposition effect of these investors for

[10] See, for instance, the following link for more details: https://en.wikipedia.org/wiki/Migration_in_China.

each region of origin. We then link social trust in the region of origin to their corresponding flows and the disposition effect following the same approach described in Section III.

We tabulate the results in Panel A of Table 5 for migrant investors located in the aforementioned top three host regions. Panel B reports the corresponding tests for all migrant investors. Models (1) to (2), (3) to (4), and (5) to (6) present the impact of *trust-induced flows* on the disposition effect, the PSW and the PSL, respectively. In addition, Models (2), (4), (6) provide placebo tests in which we test the influence of *trust-induced flows* and *other flows* side by side.

We can see that *trust-induced flows* are still negatively associated with the disposition effect in general, whereas *other flows* are uncorrelated with the effect. In Model (2) of Panel A, for instance, a one-standard-deviation increase in *trust-induced flows* (0.031 in this subsample) is associated with a 0.028 decrease in the magnitude of the disposition effect or 43.4% compared to the average disposition effect in the sample (6.2% if compared to the standard deviation of the disposition effect in the sample). A similar pattern can be observed in Panel B for migrant investors located in all regions; a one-standard-deviation increase in *trust-induced flows* is associated with a 24% decrease in the disposition effect when scaled by the mean disposition effect.

Interestingly, between the two elements of the disposition effect, home region trust has a stronger effect on the loss side. The coefficient for PSW is not statistically significant, whereas that for the PSL is highly significant. A reduction in the disposition effect is mostly due to the increasing PSL: a one-standard-deviation increase in *trust-induced flows* is associated with a 7.81% increase in the PSL (when scaled by the unconditional mean of the PSL, which is 0.008 in Model (5) of Panel A). These results show that social norms seem to play a particularly important role in the loss aversion–related trading behaviors of migrant investors. This result is not only interesting itself but also helps justify a causal interpretation of our main results.

V. Additional Robustness Checks

In this section, we conduct four sets of robustness checks to further validate our previous results.

The first set of tests uses alternative proxies for social trust based on the WVS and donations following the 2008 Sichuan Great Earthquake. We apply our baseline test, as in Equation (2), to these two trust measures and tabulate the results in Panels A and B of Table 6. In each panel, we report the influence of *trust-induced flows* on the disposition effect, PSW, and PSL in Models (1) to (2), (3) to (4), and (5) to (6), respectively.

We find that our main conclusion holds: *trust-induced flows* significantly affect the disposition effect. Panel A shows that, although the WVS covers fewer regions than does the ZK survey, the proxies for social trust based on these measures significantly influence the disposition effect in a similar way. In particular, consistent with the mitigation hypothesis, WVS-based trust reduces the PSW and increases the PSL. Panel B shows that donation-related trust affects the disposition effect in a similar way. Unreported tests show that scaling donations by GDP yields similar results. Taken together, this table and our previous results indicate that the influence of social trust is significant regardless of how we measure it.

The second set of tests compares the behavior of retail investors to that of institutional investors. While our accounts are dominated by retail investors, 3,972 accounts are associated with institutional investors. We separately aggregate their information into regional accounts and then apply the baseline test to each group of investors. The results are reported in Table 7. Specifically, Models (1) and (2) display how *trust-induced flows* affect the disposition effect for retail investors, while Models (3) and (4) tabulate similar statistics for institutional investors.

The results for retail investors are similar to those reported in Table 3 (based on the whole sample of accounts). This is not surprising because retail accounts dominate our sample. For brevity, we do not tabulate the PSW and PSL results; they are similar to those in Table 4. The interesting observation is for institutional investors: *trust-induced flows* do not affect their disposition effect. The difference between retail and institutional investors is economically sizeable. Moreover, unreported tests show that this insignificance applies to both the PSW and the PSL. These results are intuitive: institutional investors' decisions should more closely reflect professional experience rather than cultural influences.

The third set of robustness checks concerns the impact of trust across different distribution channels. To examine this impact, we apply our main tests separately to accounts linked to each of the three major distribution channels. We report the results in Table 8; Models (1) to (2), (3) to (4), and (5) to (6) tabulate indicate the impact of *trust-induced flows* on the disposition effect for the bank channel, brokerage channel, and online channel, respectively. Interestingly, we find that that distribution channels do not affect the relationship between social trust and the disposition effect. Hence, although some distribution channels, such as banks, may create more relationship-linked flows, the influence of social norms seems to extend beyond these channels.

Overall, our results confirm the mitigation hypothesis: a higher degree of social trust can mitigate the disposition effect through enhanced flow-performance-sensitivity. Hence, the influence of social trust on investors mainly affects information considerations. Other things being equal, high-trust investors have stronger responses to information, purchasing more winners and selling more losers.

Conclusion

While both culture and behavioral biases of individual investors are regarded as important, they are largely examined as independent phenomena in the literature. In principle, however, investors' behaviors should be heavily influenced by social norms. In this paper, we document that this is indeed the case by examining two competing hypotheses on the impact of social trust on the disposition effect among mutual fund investors. On the one hand, in a more trusting culture, performance reports provided by funds are considered more credible by investors, eliciting stronger reactions to fund performance. This results in higher flow-performance sensitivity, which mitigates the tendency to sell winners and hold onto losers. On the other hand, trust reduces concerns about expropriation. This influence reduces investors' need to react to poor performance, which can signal expropriation. The resulting lower flow-performance sensitivity augments the disposition effect.

We test these competing hypotheses by exploring a proprietary dataset of complete account-level trading information for all investors in a mutual fund family in China. The disposition effect is observed among fund investors in our sample. We document that a higher degree of social trust is associated with higher flow-performance sensitivity and that trust-induced flows mitigate the disposition effect. Tests exploring the relationship between trust by region of origin imply a causal interpretation.

Our results suggest that, in addition to cognitive heuristics, social norms play an important role in the trading behavior of individual investors. In other words, the *observed* behavior of individual investors is likely to be jointly determined by cognitive heuristics and social forces. Although our findings shed new light on existing knowledge of human behavior, some questions arise. For instance, Chinese and U.S. investors seem to exhibit opposite behavioral tendencies with respect to the disposition effect. The difference between these two groups of investors suggests the need for more research to understand the influences of country-level social norms on investor behaviors.

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Appendix A

Panel A: Aggregated Account-level Variables	
Aggregate Account	Region-Channel-Fund
Region	31 different regions in China
Channel	Distribution channels of mutual funds (0, 1, and 2 represent the bank, broker, and direct channels, respectively)
Trust_ZK	Trust is the log of the trust index constructed by Zhang and Ke (2002) based on surveys asking corporate senior managers to rate the trustworthiness of firms in different provinces
Inflow%	Inflow_ratio=Total inflow in each account at time t/account_TNA at time t−1
Outflow%	Outflow_ratio=Total outflow in each account at time t/account_TNA at time t-1
Netflow%	Netflow_ratio=Total netflow in each account at time t/account_TNA at time t-1
The Disposition Effect	The disposition effect calculated by the method of Ben-David and Hirshleifer (2012): the probability of selling winners minus the probability of selling losers
PSW	The probability of selling winners aggregated at the Region-Channel-Fund account level
PSL	The probability of selling losers aggregated at the Region-Channel-Fund account level
Panel B: Fund-level Variables	
Ret	Benchmark-adjusted return: Difference between the fund monthly net return and its benchmark return.
Log(TNA)	Log total net assets of the mutual funds in millions of RMB
Mfee	Percentage of management fee as a share of total net assets of the fund
Fundage	Number of years since the fund launch
NAV	Daily net asset value of the fund
Panel C: Region-level Variables	
Log_GDP	Log of gross domestic product at year end in billions of RMB
Log_inflation	Log of inflation rate for each month
Log_import	Log of imports at month end in millions of U.S. dollars
Log_export	Log of export at month end in millions of U.S. dollars
Unemploymentrate	Unemployment rate at year end for each region
Log_pop	Log of total population at year end
Log_gov_exp	Log of total government expenditure at year end in billions of RMB
Log_num_state_firms	Log of number of state-owned firms at year end
Log_num_private_firms	Log of number of private firms at year end
Log_num_employ_public	Log of number of employees working for public firms
Log_num_employ_private	Log of number of employees working for private firms
Log_residence_income	Log of average dispensable residence income at year end in RMB
Log_bank_saving	Log of total residence bank savings at year end in billions of RMB
Panel D: Trust Proxy Variables	
Donation	Region-level variable describing how much money and materials the region donated after 2008 Sichuan Earthquake
Trust_WVS	Fraction of people who believe that "Most people can be trusted" in a region (World Values Survey 2001)
LD	Number of languages spoken in each region
Hill	Fraction of terrain that is hilly in each region
Ethnicity	Number of ethnicities in the region
Religion	Number of religions in the region
List_localfirm	The number of stocks headquartered in each region divided by number of all stocks in the country

Appendix B

The dataset consists of three main parts, investor account-level information, dividend distribution information and investor trade information. The investor account-level information describes an individual investor's account, including the investor's unique national identity (e.g., date of birth, age, gender, education, vocation and location) and the account status (e.g., application date, confirmation date, Internet service and bonus type). Dividend distribution information includes the amount distributed to each investor based on his/her fund holdings, and this table includes the fund code, investor ID, investor location, dividend date and bonus type. Finally, investor trade information includes all the necessary information regarding an investor's purchases and sales of the fund, which includes an investor's trade type, trade fees and channel used to purchase shares. For a complete review of the data, please refer to the following table.

Panel A: Investor Account-level Information	
CustID	Investor's ID
Birth	Investor's date of birth
Gender	1=female 2=male
Education	Investor's education level
Vocation	Investor's vocation
Confirm Date	Account confirmation date
Call Service	Whether telephone service is open
Internet Service	Whether Internet service is open
Center*	Business center
Channel*	Business channel
Region	Investor province location
Postcode	Investor location postcode
BusinFlag*	Business type
Panel B: Dividend Distribution Information	
CustID	Investor's ID
FundID	Fund code
Regdate	Registration date for the dividend
Exdate	Ex-dividend date
PayDate	Date of payment
Bonustype	0=Dividend reinvested 1=Cash dividend
Totalshare	Investor holding of the fund for dividend
Unitprofit	Dividend per share
Totalprofit	Total dividend proceed
Panel C: Investor Trading Information	
BusinFlag*	Transaction type
Cdate	Confirmation date
Balance	Application amount (cash)
Shares	Application amount (shares)
Confirmbalance	Confirmation amount (cash)
Netvalue	Net value per share (based on date)
Transactionfee*	Total transaction fees
AGIO	Discount percentage on transaction fees
Center	Business center
Channel	Business channel
Agency No.	The channel agency code
Region	Investor province location
City	Investor city location
Postcode	Investor location postcode

Table 1: Summary Statistics

This table presents summary statistics for the data used in this paper. The summary statistics are based on a sample of mutual fund investors who trade in a confidential mutual fund family in the period from September 2002 to December 2011. Panel A reports the aggregate account level statistics and all variables are taken average over the sample period for each aggregate account. Panel B and Panel D report fund and regional controls and all variables are taken average across regions and years. Panel C presents the statistics for trust, alternative proxies of trust and regional and cultural control variables. Panel E shows the correlation matrix of variables used in the regression.

Panel A: Aggregate Account-Level Variables													
Variables	n	p1	p5	p25	mean	median	p75	p90	p95	p99	Std.dev	min	max
Inflow	39869	0	0	0	0.054	0.003	0.026	0.112	0.258	0.989	0.176	0	1.996
Outflow	39869	0	0	0.003	0.066	0.019	0.065	0.190	0.311	0.649	0.124	0	1.000
Netflow	39869	-0.545	-0.230	-0.033	-0.012	-0.006	0	0.040	0.145	0.816	0.185	-0.999	1.969
The Disposition Effect	34170	-0.0772	-0.0253	-0.0012	0.0049	0.0022	0.0084	0.0238	0.0445	0.1111	0.0274	-0.2038	0.3223
PSW	35111	0.0007	0.0013	0.0039	0.0168	0.0084	0.0182	0.0392	0.0625	0.1250	0.0255	0.0001	0.3333
PSL	34969	0.0003	0.0005	0.0016	0.0118	0.0044	0.0130	0.0294	0.0479	0.1111	0.0201	0.0000	0.2045
Trust Induced Flows	36750	-0.056	-0.012	-0.002	0.002	0.000	0.005	0.013	0.024	0.068	0.018	-0.191	0.195
Panel B: Fund-Level Variables													
Ret	39869	-0.075	-0.045	-0.011	0.006	0.005	0.024	0.046	0.062	0.084	0.032	-0.103	0.126
Channel	39869	0	0	0	0.979	1	2	2	2	2	0.827	0	2
Log(TNA)	39869	19.181	20.044	21.054	21.876	22.125	22.757	23.083	23.209	23.522	1.066	19.010	23.577
Fundage	39869	4.159	5.112	6.529	6.934	7.165	7.551	7.803	7.932	8.102	0.867	3.807	8.139
Panel C: Trust and Alternative Proxies													
Trust	39869	0.993	1.411	2.451	3.028	2.741	3.469	4.777	5.13	5.389	1.09	0.993	5.389
Edonation	39869	0	0.001	1.96	6.833	4.74	8.05	17.68	25.24	37.92	8.183	0	37.92
LD	39127	1	1	1	1.973	1	2	4	5	6	1.349	1	6
Hill	39127	0	0.01	0.08	0.179	0.18	0.22	0.39	0.41	0.47	0.125	0	0.47
Ethnicity	39127	0.36	0.38	0.72	0.820	0.92	0.98	0.99	0.99	0.99	0.201	0.36	0.99
Religion	39127	0.02	0.07	0.17	0.264	0.23	0.39	0.45	0.49	0.59	0.135	0.02	0.59
Panel D: Region-Level Variables													
Log_GDP	39483	2.784	3.800	5.201	5.901	6.027	6.706	7.290	7.619	8.145	1.153	1.490	8.434
Log_pop	39869	5.678	6.391	7.785	8.116	8.246	8.719	9.087	9.152	9.223	0.810	5.574	9.253
Log_residence_income	39869	8.783	8.950	9.241	9.480	9.484	9.667	9.932	10.082	10.278	0.330	8.569	10.368
Log_bank_saving	39869	5.220	6.420	7.988	8.423	8.536	9.076	9.574	9.855	10.355	0.994	3.916	10.500
Log_inflation	39869	4.578	4.593	4.619	4.639	4.639	4.661	4.675	4.685	4.705	0.028	4.562	4.733
Log_import	38689	1.243	3.834	5.706	6.682	6.398	7.893	9.361	9.803	10.242	1.809	-1.411	10.467
Log_export	38563	3.212	4.036	5.653	6.847	6.661	8.140	9.391	9.848	10.518	1.745	1.482	10.787
Unemploymentrate	39431	1.430	2.560	3.480	3.758	3.870	4.180	4.300	4.400	5.100	0.627	1.180	6.500
Log_gov_exp	39869	5.077	5.643	6.591	7.065	7.168	7.580	7.945	8.103	8.500	0.743	4.369	8.598
Log_num_state_firms	39869	3.611	4.762	6.250	6.466	6.593	6.917	7.188	7.305	7.605	0.726	3.497	7.957
Log_num_private_firms	39869	-0.734	0.631	1.964	2.544	2.550	3.208	3.910	4.144	4.552	1.033	-2.303	4.652
Log_num_employ_public	38964	3.010	4.045	5.491	5.757	5.886	6.235	6.600	6.804	6.961	0.793	2.855	7.020
Log_num_employ_private	39857	3.384	4.063	5.117	5.726	5.835	6.296	6.827	7.113	7.482	0.895	2.139	7.603

Variables	*Inflow*	*Outflow*	*Netflow*	*Lag_ret*	*Log(TNA)*	*Fundage*	*Log_GDP*	*Log_pop*	*Trust*	*Disposition*	*Trust-induced flows*
Inflow	1										
Outflow	0.296	1									
Netflow	0.776	-0.373	1								
Lag_ret	0.128	0.058	0.086	1							
Log(TNA)	-0.055	-0.136	0.036	-0.088	1						
Fundage	-0.133	-0.235	0.026	-0.069	0.129	1					
Log_GDP	-0.022	-0.084	0.034	-0.020	0.045	0.168	1				
Log_pop	0.000	0.020	-0.014	0.004	-0.044	-0.002	0.694	1			
Trust	0.017	0.024	0.001	0.008	-0.068	-0.027	0.624	0.380	1		
The Disposition Effect	-0.065	-0.105	0.005	-0.054	0.132	0.066	0.025	-0.025	-0.043	1	
Trust-induced flows	0.153	0.055	0.112	0.623	-0.105	-0.020	0.001	0.017	0.049	-0.045	1
Other flows	0.765	-0.381	0.995	0.025	0.047	0.041	0.035	-0.016	-0.004	0.010	0.014

Table 2: The Impact of Trust on Flow Performance Sensitivity

This table presents the results of the following monthly panel regressions with time, fund, region fixed effects and standard errors clustered at the regional level:

$$Netflow_{g,i,f,t} = \alpha + \beta \times Ret_{f,t-1} + \delta \times Trust_g + \gamma \times Trust_g \times Ret_{f,t-1} + C \times M_{g,i,f,t-1} + \varepsilon_{g,i,f,t},$$

where $Netflow_{g,i,f,t}$ is the net flow ratio of the aggregate account of region g, channel i, and fund f in period t; $Ret_{f,t-1}$, is the return of fund f in access of the market in the previous month; $Trust_g$ is the logarithm of trust index in region *g*; Ch_i refers to the distribution channel *i* for fund *f* at month *t-1*; and $M_{g,i,f,t-1}$ is a vector of fund-level control variables, including Ch_i, the influences of the distribution channels, *Lag_netflow*, the aggregate mutual fund flow at month *t-1*, *Log(TNA),* the logarithm of total net assets of fund *f* at month *t-1*, and *Fundage*, the logarithm of number of operating days since fund inception. We estimate a panel specification with fund, time, and region fixed effects, and the standard errors are clustered at the region level. Appendix A provides more detailed variable definitions. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively. The sample period is from 2002 to 2011.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Dependent Variable= Netflow					
Lag_ret	0.438	0.438	0.163	0.163	0.167	0.131
	(10.77)***	(10.76)***	(2.02)**	(2.02)**	(2.07)**	(1.48)
Trust_ZK		0.001	0.001	0.001	0.004	-0.001
		(1.03)	(0.55)	(0.55)	(14.24)***	(-0.06)
Trust*ret			0.091	0.091	0.090	0.099
			(3.57)***	(3.56)***	(3.53)***	(3.59)***
Channel				0.001	0.001	0.001
				(0.95)	(0.98)	(1.12)
Lag_netflow	0.120	0.119	0.119	0.119	0.118	0.123
	(10.74)***	(10.75)***	(10.72)***	(10.73)***	(10.67)***	(11.75)***
Log(TNA)	-0.016	-0.016	-0.016	-0.016	-0.016	-0.018
	(-9.20)***	(-9.21)***	(-9.17)***	(-9.20)***	(-9.19)***	(-9.19)***
Fundage	0.026	0.026	0.026	0.026	0.026	0.022
	(6.41)***	(6.39)***	(6.40)***	(6.39)***	(6.33)***	(4.71)***
Constant	0.205	0.202	0.202	0.201	0.191	-0.448
	(4.67)***	(4.57)***	(4.59)***	(4.56)***	(4.32)***	(-0.72)
Observations	39,315	39,315	39,315	39,315	39,315	36,097
Number of id	554	554	554	554	554	517
TIME FE	YES	YES	YES	YES	YES	YES
FUND FE	YES	YES	YES	YES	YES	YES
REGION CLUSTER	NO	NO	NO	NO	YES	YES
REGION FE	NO	NO	NO	NO	YES	YES
REGION CONTROLS	NO	NO	NO	NO	NO	YES
r2_o	0.139	0.139	0.139	0.139	0.140	0.143

Table 3: The Relationship between Trust Induced Flow and the Disposition Effect

This table presents the baseline relationship between *trust-induced flows* and the disposition effect. We first estimate *trust-induced flows* based on the following specification:

$$Netflow_{g,i,f,t} = \alpha + \beta \times Ret_{f,t-1} + \delta \times Trust_g + \gamma \times Trust_g \times Ret_{f,t-1} + C \times M_{g,i,f,t-1} + \varepsilon_{g,i,f,t},$$

where all the variables are defined as in Table 2. For any given month t, we use a 12-month rolling window prior to the month to estimate the coefficients. We then define trust-induced flows as $\widehat{Flow}^{Trust}_{g,i,f,t|t-1} = \hat{\gamma} \times Trust_g \times Ret_{f,t-1}$, where $\hat{\gamma}$ is the estimated coefficient of the interaction term in the rolling window from $t-12$ to $t-1$. The difference between realized flows in the month and trust-induced flows is then defined as other flows, denoted $\widehat{Flow}^{Other}_{g,i,f,t}$. We then regress the out-of-sample estimated disposition effect on trust-induced flows in the following panel specification:

$$Disposition_{g,i,f,t} = a + b \times \widehat{Flow}^{Trust}_{g,i,f,t|t-1} + c \times \widehat{Flow}^{Other}_{g,i,f,t} + d \times M_{g,i,f,t} + \varepsilon_{g,i,f,t},$$

where $Disposition_{g,i,f,t}$ refers to the disposition effect of the aggregate account of region g, channel i, and fund *f* in period t, $\widehat{Flow}^{Trust}_{g,i,f,t|t-1}$ and $\widehat{Flow}^{Other}_{g,i,f,t}$ are trust-induced flows and other flows, respectively, and $M_{g,i,f,t}$ is a vector of region-level control variables for each region. We further control for time, fund, and region fixed effects and cluster the standard errors at the region level. In Models (1) to (2), Models (3) to (4) and Models (5) to (6), trust-induced flows are estimated over a 12-month rolling window, a 6-month rolling window, and the entire sample, respectively. Appendix A provides more detailed variable definition. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively. The sample period is from 2002 to 2011.

Dependent Variable = The Disposition Effect						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	12 Month Rolling		6 Month Rolling		Entire Sample	
Trust Induced Flow	-0.076	-0.075	-0.059	-0.058	-0.069	-0.068
	(-5.48)***	(-5.45)***	(-5.39)***	(-5.44)***	(-4.91)***	(-4.94)***
Other Flow		0.001		0.001		0.001
		(1.18)		(1.19)		(1.10)
Log_GDP	0.003	0.003	0.003	0.003	0.003	0.003
	(1.00)	(1.00)	(0.88)	(0.99)	(0.85)	(0.96)
Log_pop	-0.021	-0.021	-0.026	-0.021	-0.026	-0.021
	(-1.12)	(-1.12)	(-1.43)	(-1.12)	(-1.43)	(-1.11)
Log_residence_income	0.015	0.015	0.011	0.015	0.012	0.015
	(1.04)	(1.04)	(0.74)	(1.03)	(0.76)	(1.05)
Log_bank_saving	0.000	0.000	0.001	0.000	0.001	0.000
	(0.04)	(0.04)	(0.05)	(0.03)	(0.05)	(0.03)
Log_inflation	0.064	0.064	0.066	0.064	0.064	0.062
	(2.07)**	(2.06)**	(2.11)**	(2.05)**	(2.06)**	(2.01)**
Log_import	0.000	0.000	0.001	0.000	0.001	0.000
	(0.45)	(0.44)	(0.67)	(0.42)	(0.68)	(0.42)
Log_export	0.002	0.002	0.002	0.002	0.002	0.002
	(1.91)*	(1.90)*	(2.39)**	(1.92)*	(2.34)**	(1.87)*
Unemploymentrate	0.003	0.003	0.003	0.003	0.003	0.003
	(2.57)**	(2.57)**	(2.41)**	(2.57)**	(2.40)**	(2.57)**
Log_gov_exp	0.006	0.006	0.005	0.006	0.005	0.006
	(1.08)	(1.08)	(0.85)	(1.10)	(0.84)	(1.09)
Log_num_state_firms	-0.007	-0.007	-0.008	-0.007	-0.008	-0.007
	(-1.94)*	(-1.93)*	(-2.39)**	(-1.93)*	(-2.41)**	(-1.94)*
Log_num_private_firms	-0.006	-0.006	-0.007	-0.006	-0.007	-0.006
	(-1.30)	(-1.30)	(-1.71)*	(-1.31)	(-1.69)*	(-1.29)
Log_num_employ_public	0.004	0.004	0.004	0.004	0.004	0.004
	(1.07)	(1.06)	(1.30)	(1.06)	(1.32)	(1.08)
Log_num_employ_private	-0.000	-0.000	-0.002	-0.000	-0.002	-0.000
	(-0.14)	(-0.14)	(-0.86)	(-0.14)	(-0.87)	(-0.14)
Constant	-0.273	-0.272	-0.183	-0.271	-0.178	-0.266
	(-1.40)	(-1.39)	(-0.93)	(-1.38)	(-0.90)	(-1.35)
Observations	31,761	31,761	30,736	31,761	30,736	31,761
Number of id	511	511	493	511	493	511
FUND FE	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES
REGION FE	YES	YES	YES	YES	YES	YES
REGION CLUSTER	YES	YES	YES	YES	YES	YES
r2_o	0.130	0.130	0.132	0.130	0.131	0.129

Table 4: The Relationship between Trust Induced Flow and PSW & PSL

This table presents the relationships between *trust-induced flows* and PSW & PSL. We first estimate *trust-induced flows* based on the following specification:

$$Netflow_{g,i,f,t} = \alpha + \beta \times Ret_{f,t-1} + \delta \times Trust_g + \gamma \times Trust_g \times Ret_{f,t-1} + C \times M_{g,i,f,t-1} + \varepsilon_{g,i,f,t},$$

where all the variables are defined as in Table 2. For a given month t, we use a 12-month rolling window prior to the month to estimate the coefficients. We then define trust-induced flows as $\widehat{Flow}^{Trust}_{g,i,f,t|t-1} = \hat{\gamma} \times Trust_g \times Ret_{f,t-1}$, where $\hat{\gamma}$ is the estimated coefficient of the interaction term in the rolling window from $t-12$ to $t-1$. The difference between realized flows in the month and trust-induced flows is defined as other flows, denoted $\widehat{Flow}^{Other}_{g,i,f,t}$. We then regress the out-of-sample estimated PSW and PSL on trust-induced flows using the following panel specification:

$$PSW_{g,i,f,t}\ or\ PSL_{g,i,f,t} = a + b \times \widehat{Flow}^{Trust}_{g,i,f,t-1} + c \times \widehat{Flow}^{Other}_{g,i,f,t-1} + d \times M_{g,t-1} + \varepsilon_{g,i,f,t},$$

where $PSW_{g,i,f,t}$ is the probability of selling winners, and $PSL_{g,i,f,t}$ the probability of selling losers in region g, channel i, and fund f in period t; $\widehat{Flow}^{Trust}_{g,i,f,t|t-1}$ and $\widehat{Flow}^{Other}_{g,i,f,t}$ are trust-induced flows and other flows, respectively, and $M_{g,i,f,t}$ is a vector of region-level control variables for each region. We further control for time, fund, and region fixed effects and cluster the standard errors at the region level. In Models (1) to (4), Models (5) to (8) and Models (9) to (12), trust-induced flows are estimated over a 12-month rolling window, a 6-month rolling window, and the entire sample, respectively. Appendix A provides more detailed variable definitions. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively. The sample period is from 2002 to 2011.

	12 Month Rolling				6 Month Rolling				Entire Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	PSW		PSL		PSW		PSL		PSW		PSL	
Trust Induced Flow	-0.058	-0.061	0.017	0.017	-0.048	-0.048	0.015	0.015	-0.030	-0.030	0.045	0.045
	(-4.32)***	(-4.59)***	(2.66)***	(1.89)*	(-4.64)***	(-4.46)***	(2.73)***	(2.09)**	(-1.95)*	(-1.99)**	(4.47)***	(3.71)***
Other Flow		-0.005		-0.006		-0.005		-0.007		-0.005		-0.007
		(-5.94)***		(-7.05)***		(-5.94)***		(-7.09)***		(-5.99)***		(-7.13)***
Log_GDP	0.003	0.001	-0.002	-0.004	0.003	0.001	-0.002	-0.004	0.003	0.001	-0.002	-0.004
	(1.27)	(0.43)	(-0.58)	(-1.10)	(1.27)	(0.43)	(-0.59)	(-1.10)	(1.23)	(0.39)	(-0.58)	(-1.09)
Log_pop	-0.002	-0.000	0.029	0.026	-0.002	-0.000	0.029	0.026	-0.002	0.000	0.029	0.026
	(-0.17)	(-0.01)	(1.79)*	(1.66)*	(-0.16)	(-0.00)	(1.79)*	(1.66)*	(-0.16)	(0.00)	(1.79)*	(1.67)*
Log_residence_income	0.011	0.010	0.007	0.002	0.011	0.010	0.007	0.002	0.011	0.010	0.007	0.002
	(1.15)	(1.04)	(0.37)	(0.13)	(1.14)	(1.03)	(0.38)	(0.13)	(1.15)	(1.04)	(0.37)	(0.12)
Log_bank_saving	-0.002	-0.004	-0.003	-0.005	-0.002	-0.004	-0.003	-0.005	-0.002	-0.004	-0.003	-0.005
	(-0.28)	(-0.44)	(-0.34)	(-0.47)	(-0.29)	(-0.45)	(-0.34)	(-0.47)	(-0.30)	(-0.46)	(-0.34)	(-0.47)
Log_inflation	0.030	0.028	-0.042	-0.041	0.030	0.028	-0.042	-0.041	0.029	0.027	-0.042	-0.041
	(1.39)	(1.32)	(-1.61)	(-1.60)	(1.39)	(1.32)	(-1.61)	(-1.60)	(1.33)	(1.27)	(-1.61)	(-1.60)
Log_import	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.83)	(0.95)	(0.38)	(0.74)	(0.80)	(0.92)	(0.39)	(0.75)	(0.81)	(0.93)	(0.38)	(0.74)
Log_export	0.001	0.001	-0.000	0.000	0.001	0.001	-0.000	0.000	0.001	0.001	-0.000	0.000
	(1.63)	(1.72)*	(-0.35)	(0.29)	(1.65)*	(1.74)*	(-0.36)	(0.28)	(1.63)	(1.71)*	(-0.32)	(0.32)
Unemploymentrate	0.001	0.001	-0.001	-0.001	0.001	0.001	-0.001	-0.001	0.001	0.001	-0.001	-0.001
	(1.07)	(0.96)	(-0.98)	(-1.12)	(1.07)	(0.95)	(-0.98)	(-1.12)	(1.06)	(0.95)	(-0.97)	(-1.11)
Log_gov_exp	0.001	0.003	-0.004	-0.004	0.001	0.003	-0.004	-0.004	0.001	0.003	-0.004	-0.004
	(0.29)	(0.58)	(-0.78)	(-0.80)	(0.30)	(0.60)	(-0.79)	(-0.81)	(0.29)	(0.59)	(-0.78)	(-0.81)
Log_num_state_firms	-0.004	-0.004	0.004	0.002	-0.004	-0.004	0.004	0.002	-0.004	-0.004	0.004	0.002
	(-1.91)*	(-2.10)**	(1.11)	(0.63)	(-1.91)*	(-2.09)**	(1.11)	(0.63)	(-1.94)*	(-2.12)**	(1.11)	(0.64)
Log_num_private_firms	-0.008	-0.009	0.002	0.000	-0.008	-0.009	0.002	0.000	-0.008	-0.009	0.002	0.000
	(-1.50)	(-1.61)	(0.40)	(0.03)	(-1.50)	(-1.61)	(0.41)	(0.03)	(-1.50)	(-1.61)	(0.40)	(0.02)
Log_num_employ_public	0.001	0.002	0.000	0.001	0.001	0.002	0.000	0.001	0.001	0.002	0.000	0.001
	(0.38)	(0.51)	(0.05)	(0.31)	(0.38)	(0.52)	(0.05)	(0.31)	(0.39)	(0.53)	(0.05)	(0.35)
Log_num_employ_private	0.006	0.007	0.007	0.006	0.006	0.007	0.007	0.006	0.006	0.007	0.007	0.006
	(2.60)***	(2.70)***	(3.53)***	(3.09)***	(2.60)***	(2.70)***	(3.53)***	(3.09)***	(2.58)***	(2.69)***	(3.53)***	(3.11)***
Constant	-0.196	-0.179	-0.101	-0.002	-0.195	-0.178	-0.100	-0.002	-0.190	-0.175	-0.102	0.000
	(-1.09)	(-1.06)	(-0.45)	(-0.01)	(-1.09)	(-1.06)	(-0.45)	(-0.01)	(-1.06)	(-1.03)	(-0.45)	(0.00)
Observations	31,391	32,434	31,331	32,366	31,391	32,434	31,331	32,366	31,391	32,434	31,331	32,375
Number of id	494	512	495	513	494	512	495	513	494	512	495	513
FUND FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
REGION FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
REGION CLUSTER	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
r2_o	0.171	0.170	0.230	0.230	0.170	0.170	0.230	0.230	0.170	0.170	0.230	0.230

Table 5: The Impact of Trust Induced Flow on Migrant Investors (Endogeneity Test)

This table tests the relationship between *trust-induced flows* and the disposition effect for endogeneity for migrant investors. We use National Identity Numbers to trace the regions of birth of the investors and treat them as their regions of origin in terms of social trust. Then, for each region of origin, we aggregate the trading behavior of the investors that migrated from it, which allows us to construct variables describing both the flow information and the disposition effect of these investors for each region of origin. We then link social trust in the region of origin to their corresponding flows and the disposition effects following the same approach as in Table 3. Panel A reports the results for migrant investors located in the top three regions, while Panel B reports the results for all migrant investors. Specifically, we first estimate *trust-induced flows* based on the following specification for migrant accounts:

$$Netflow_{g,i,f,t} = \alpha + \beta \times Ret_{f,t-1} + \delta \times Trust_g + \gamma \times Trust_g \times Ret_{f,t-1} + C \times M_{g,i,f,t-1} + \varepsilon_{g,i,f,t},$$

where all the variables are as defined in Table 2. For any given month t, we use a 12-month rolling window prior to the month to estimate the coefficients. We then define trust-induced flows as $\widehat{Flow}^{Trust}_{g,i,f,t|t-1} = \hat{\gamma} \times Trust_g \times Ret_{f,t-1}$, where $\hat{\gamma}$ is the estimated coefficient of the interaction term in the rolling window from $t-12$ to $t-1$. The difference between realized flows in the month and trust-induced flows is then defined as other flows, denoted $\widehat{Flow}^{Other}_{g,i,f,t}$. We then regress the out-of-sample estimated disposition effect on trust-induced flows in the following panel specification:

$$Disposition_{g,i,f,t} = a + b \times \widehat{Flow}^{Trust}_{g,i,f,t|t-1} + c \times \widehat{Flow}^{Other}_{g,i,f,t} + d \times M_{g,i,f,t} + \varepsilon_{g,i,f,t},$$

where $Disposition_{g,i,f,t}$ refers to the disposition effect of the aggregate account of migrant investors in region g, channel i, and fund f in period t, $\widehat{Flow}^{Trust}_{g,i,f,t|t-1}$ and $\widehat{Flow}^{Other}_{g,i,f,t}$ are trust-induced flows and other flows, respectively, and $M_{g,i,f,t}$ is a vector of region-level control variables for each region. We further control for time, fund, and region fixed effects and cluster the standard errors at the region level. Appendix A provides more detailed variable definitions. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively. The sample period is from 2002 to 2011.

Panel A: Top 3 City Migrates						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	The Disposition Effect		PSW		PSL	
Trust Induced Flow	-0.028	-0.028	-0.002	-0.002	0.026	0.026
	(-4.97)***	(-4.99)***	(-0.56)	(-0.56)	(4.54)***	(4.56)***
Other Flow		0.000		-0.000		-0.000
		(0.02)		(-0.06)		(-0.01)
Log_GDP	-0.002	-0.002	-0.000	-0.000	0.002	0.002
	(-0.80)	(-0.80)	(-0.14)	(-0.14)	(0.54)	(0.54)
Log_pop	0.032	0.032	0.020	0.020	-0.010	-0.010
	(3.35)***	(3.31)***	(2.31)**	(2.29)**	(-1.36)	(-1.36)
Log_residence_income	0.032	0.032	0.027	0.027	-0.008	-0.008
	(4.69)***	(4.68)***	(3.36)***	(3.34)***	(-0.75)	(-0.75)
Log_bank_saving	0.004	0.004	0.001	0.001	-0.003	-0.003
	(0.52)	(0.53)	(0.18)	(0.18)	(-0.39)	(-0.39)
Log_inflation	0.010	0.010	0.029	0.029	0.014	0.014
	(0.59)	(0.59)	(1.31)	(1.31)	(0.98)	(0.98)
Log_import	-0.001	-0.001	0.002	0.002	0.002	0.002
	(-0.87)	(-0.87)	(2.26)**	(2.26)**	(2.21)**	(2.21)**
Log_export	-0.001	-0.001	-0.001	-0.001	-0.000	-0.000
	(-0.77)	(-0.77)	(-0.46)	(-0.46)	(-0.13)	(-0.13)
Unemploymentrate	0.003	0.003	0.002	0.002	-0.001	-0.001
	(4.50)***	(4.52)***	(2.97)***	(2.98)***	(-1.57)	(-1.57)
Log_gov_exp	-0.003	-0.003	-0.002	-0.002	0.004	0.004
	(-0.70)	(-0.70)	(-0.43)	(-0.44)	(1.06)	(1.06)
Log_num_state_firms	0.004	0.004	0.003	0.003	-0.001	-0.001
	(1.83)*	(1.83)*	(1.11)	(1.11)	(-0.63)	(-0.63)
Log_num_private_firms	0.008	0.008	0.005	0.005	-0.003	-0.003
	(1.89)*	(1.89)*	(1.32)	(1.32)	(-0.98)	(-0.98)
Log_num_employ_public	-0.008	-0.008	0.000	0.000	0.007	0.007
	(-1.64)	(-1.64)	(0.11)	(0.11)	(1.31)	(1.31)
Log_num_employ_private	0.002	0.002	-0.000	-0.000	-0.002	-0.002
	(0.46)	(0.47)	(-0.01)	(-0.01)	(-0.73)	(-0.74)
Constant	-0.640	-0.641	-0.537	-0.536	0.129	0.129
	(-4.68)***	(-4.69)***	(-3.11)***	(-3.09)***	(0.86)	(0.86)
Observations	5,779	5,779	5,842	5,842	5,910	5,910
Number of id	325	325	330	330	350	350
FUND FE	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES
REGION FE	YES	YES	YES	YES	YES	YES
REGION CLUSTER	YES	YES	YES	YES	YES	YES
r2_o	0.142	0.142	0.327	0.327	0.456	0.456

Panel B: All City Migrates						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	The Disposition Effect		PSW		PSL	
Trust Induced Flow	-0.006	-0.006	-0.001	-0.001	0.005	0.005
	(-4.48)***	(-4.44)***	(-1.06)	(-1.05)	(4.85)***	(4.85)***
Other Flow		0.000		0.000		-0.000
		(1.25)		(0.36)		(-1.41)
Log_GDP	0.002	0.002	-0.001	-0.001	-0.002	-0.002
	(0.56)	(0.58)	(-0.45)	(-0.44)	(-0.83)	(-0.85)
Log_pop	-0.013	-0.013	0.001	0.001	0.014	0.014
	(-1.68)*	(-1.68)*	(0.15)	(0.15)	(2.12)**	(2.12)**
Log_residence_income	0.029	0.029	0.032	0.032	0.004	0.004
	(2.75)***	(2.80)***	(5.07)***	(5.10)***	(0.39)	(0.37)
Log_bank_saving	0.005	0.005	0.001	0.001	-0.004	-0.004
	(0.69)	(0.73)	(0.22)	(0.23)	(-0.63)	(-0.66)
Log_inflation	0.002	0.002	0.003	0.003	-0.002	-0.002
	(0.09)	(0.09)	(0.19)	(0.19)	(-0.13)	(-0.13)
Log_import	0.001	0.001	0.001	0.001	0.000	0.000
	(0.73)	(0.73)	(2.14)**	(2.14)**	(0.80)	(0.78)
Log_export	-0.002	-0.002	-0.002	-0.002	0.000	0.000
	(-1.37)	(-1.38)	(-1.70)*	(-1.70)*	(0.28)	(0.28)
Unemploymentrate	0.002	0.002	0.001	0.001	-0.001	-0.001
	(2.03)**	(2.03)**	(2.12)**	(2.12)**	(-1.07)	(-1.07)
Log_gov_exp	-0.007	-0.007	-0.006	-0.006	0.001	0.001
	(-1.53)	(-1.54)	(-2.45)**	(-2.45)**	(0.18)	(0.20)
Log_num_state_firms	-0.001	-0.001	0.001	0.001	0.002	0.002
	(-0.36)	(-0.33)	(0.88)	(0.88)	(0.78)	(0.76)
Log_num_private_firms	0.011	0.011	0.009	0.009	-0.001	-0.001
	(2.61)***	(2.63)***	(3.35)***	(3.36)***	(-0.38)	(-0.40)
Log_num_employ_public	0.009	0.009	0.008	0.008	0.000	0.000
	(3.42)***	(3.47)***	(3.59)***	(3.61)***	(0.05)	(0.03)
Log_num_employ_private	-0.008	-0.008	-0.006	-0.006	0.002	0.002
	(-2.56)**	(-2.55)**	(-2.65)***	(-2.64)***	(0.89)	(0.88)
Constant	-0.180	-0.185	-0.290	-0.290	-0.113	-0.109
	(-2.00)**	(-2.05)**	(-3.82)***	(-3.85)***	(-1.06)	(-1.02)
Observations	11,297	11,297	11,423	11,423	11,422	11,422
Number of id	419	419	431	431	429	429
FUND FE	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES
REGION FE	YES	YES	YES	YES	YES	YES
REGION CLUSTER	YES	YES	YES	YES	YES	YES
r2_o	0.122	0.122	0.266	0.266	0.346	0.346

Table 6: The Impact of Alternative Proxies of Trust

This table reports the relationships between alternative trust proxies and the disposition effect. In Panel A, $Donation$ refers to the money and materials people from a region donated after the 2008 Sichuan Earthquake, scaled by the population of the region. In Panel B, $WVS\ Trust$ refers to the fraction of World Values Survey (2001) respondents who believe that "Most people can be trusted" in a region. In each panel, we report the influence of *trust-induced flows* on the disposition effect, PSW, and PSL in Models (1) to (2), (3) to (4), and (5) to (6), respectively. Appendix A provides more detailed variable definitions. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively. The sample period is from 2002 to 2011.

Panel A: Second Stage Regression of Donation Induced Flow on the Disposition Effect						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	The Disposition Effect		PSW		PSL	
Donation Induced Flow	-0.056	-0.056	-0.053	-0.053	-0.002	-0.003
	(-2.45)**	(-2.44)**	(-2.30)**	(-2.36)**	(-0.11)	(-0.15)
Other Flow		0.001		-0.005		-0.007
		(1.15)		(-5.48)***		(-6.75)***
Log_GDP	0.002	0.002	0.001	0.001	-0.002	-0.002
	(0.66)	(0.65)	(0.42)	(0.43)	(-0.55)	(-0.53)
Log_pop	-0.020	-0.020	-0.001	-0.001	0.022	0.022
	(-0.96)	(-0.96)	(-0.11)	(-0.10)	(1.29)	(1.28)
Log_residence_income	0.007	0.007	0.007	0.007	-0.001	-0.002
	(0.43)	(0.43)	(0.60)	(0.58)	(-0.08)	(-0.09)
Log_bank_saving	-0.001	-0.001	-0.006	-0.006	-0.006	-0.006
	(-0.05)	(-0.05)	(-0.73)	(-0.73)	(-0.55)	(-0.55)
Log_inflation	0.061	0.060	0.021	0.022	-0.040	-0.037
	(1.71)*	(1.70)*	(0.95)	(1.02)	(-1.33)	(-1.26)
Log_import	-0.000	-0.000	0.000	0.000	0.001	0.001
	(-0.04)	(-0.04)	(0.70)	(0.75)	(1.22)	(1.25)
Log_export	0.001	0.001	0.001	0.001	-0.000	-0.000
	(1.41)	(1.40)	(1.32)	(1.35)	(-0.11)	(-0.03)
Unemploymentrate	0.002	0.002	0.001	0.001	-0.001	-0.001
	(2.12)**	(2.12)**	(1.02)	(0.98)	(-0.51)	(-0.58)
Log_gov_exp	0.006	0.006	0.004	0.004	-0.003	-0.003
	(1.00)	(1.00)	(0.70)	(0.72)	(-0.58)	(-0.54)
Log_num_state_firms	-0.007	-0.007	-0.005	-0.005	0.001	0.001
	(-1.90)*	(-1.89)*	(-2.66)***	(-2.72)***	(0.34)	(0.30)
Log_num_private_firms	-0.005	-0.005	-0.012	-0.012	-0.003	-0.004
	(-0.84)	(-0.84)	(-2.20)**	(-2.23)**	(-0.81)	(-0.85)
Log_num_employ_public	0.003	0.003	0.001	0.001	0.000	0.000
	(0.74)	(0.74)	(0.36)	(0.37)	(0.01)	(0.01)
Log_num_employ_private	0.000	0.000	0.007	0.007	0.006	0.006
	(0.11)	(0.12)	(2.61)***	(2.62)***	(2.84)***	(2.80)***
Constant	-0.181	-0.179	-0.087	-0.093	0.070	0.062
	(-0.82)	(-0.81)	(-0.51)	(-0.54)	(0.29)	(0.26)
Observations	28,426	28,426	29,018	29,018	28,960	28,960
Number of id	457	457	458	458	459	459
FUND FE	YES	YES	YES	YES	YES	YES
REGION FE	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES
REGION CLUSTER	YES	YES	YES	YES	YES	YES
r2_o	0.123	0.123	0.170	0.172	0.224	0.228

Panel B: Second Stage Regression of WVS Trust Induced Flow on the Disposition Effect						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	The Disposition Effect		PSW		PSL	
WVS Trust Induced Flow	-0.050	-0.048	-0.033	-0.037	0.024	0.019
	(-3.30)***	(-3.21)***	(-2.62)***	(-2.91)***	(2.43)**	(1.98)**
Other Flow		0.002		-0.006		-0.008
		(1.95)*		(-7.95)***		(-8.29)***
Log_GDP	0.001	0.001	-0.001	-0.001	-0.003	-0.003
	(0.40)	(0.39)	(-0.32)	(-0.30)	(-0.74)	(-0.71)
Log_pop	-0.014	-0.014	0.016	0.016	0.030	0.030
	(-0.57)	(-0.58)	(1.19)	(1.22)	(1.53)	(1.55)
Log_residence_income	0.014	0.014	0.014	0.014	-0.002	-0.003
	(0.74)	(0.75)	(1.02)	(0.99)	(-0.10)	(-0.13)
Log_bank_saving	0.007	0.007	-0.003	-0.003	-0.006	-0.006
	(0.53)	(0.53)	(-0.28)	(-0.29)	(-0.53)	(-0.54)
Log_inflation	0.039	0.038	-0.012	-0.010	-0.058	-0.055
	(1.00)	(0.99)	(-0.66)	(-0.56)	(-1.84)*	(-1.77)*
Log_import	0.002	0.002	0.001	0.001	-0.000	-0.000
	(1.68)*	(1.67)*	(1.12)	(1.12)	(-0.54)	(-0.51)
Log_export	0.000	0.000	0.000	0.000	0.000	0.000
	(0.38)	(0.35)	(0.39)	(0.47)	(0.05)	(0.17)
Unemploymentrate	0.002	0.002	0.001	0.001	-0.001	-0.001
	(1.57)	(1.57)	(0.72)	(0.69)	(-0.57)	(-0.63)
Log_gov_exp	0.012	0.012	0.004	0.004	-0.007	-0.007
	(1.53)	(1.52)	(0.62)	(0.68)	(-0.97)	(-0.94)
Log_num_state_firms	-0.011	-0.011	-0.002	-0.003	0.008	0.008
	(-2.77)***	(-2.75)***	(-0.79)	(-0.83)	(2.16)**	(2.11)**
Log_num_private_firms	-0.005	-0.005	-0.006	-0.006	-0.002	-0.002
	(-1.23)	(-1.21)	(-0.94)	(-0.97)	(-0.33)	(-0.34)
Log_num_employ_public	0.004	0.004	-0.001	-0.001	-0.003	-0.003
	(0.90)	(0.90)	(-0.57)	(-0.57)	(-0.72)	(-0.73)
Log_num_employ_private	0.000	0.000	0.008	0.008	0.007	0.007
	(0.05)	(0.07)	(3.24)***	(3.20)***	(3.44)***	(3.35)***
Constant	-0.258	-0.256	-0.168	-0.179	0.094	0.086
	(-0.97)	(-0.96)	(-0.76)	(-0.79)	(0.32)	(0.29)
Observations	26,638	26,638	27,128	27,128	27,063	27,063
Number of id	423	423	423	423	424	424
FUND FE	YES	YES	YES	YES	YES	YES
REGION FE	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES
REGION CLUSTER	YES	YES	YES	YES	YES	YES
r2_o	0.147	0.147	0.177	0.178	0.238	0.242

Table 7: The Relationship between Trust Induced Flow and the Disposition Effect for Individuals and Institutions

This table examines the relationship between *trust-induced flows* and the disposition effect for individual investors and institutional investors separately. Panel A presents the results for individual investors and panel B shows the 2nd stage regression results for institutional investors. Appendix A provides more detailed variable definition. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively. The sample period is from 2002 to 2011.

Dependent Variable = The Disposition Effect				
	(1)	(2)	(3)	(4)
VARIABLES	Individual Investors		Institutional Investors	
Trust Induced Flow	-0.063	-0.062	0.001	0.000
	(-4.53)***	(-3.93)***	(0.24)	(0.06)
Other Flow		0.002		-0.000
		(1.43)		(-0.33)
Log_GDP	-0.000	-0.000	0.009	0.009
	(-0.04)	(-0.06)	(0.87)	(0.95)
Log_pop	-0.022	-0.022	-0.019	-0.019
	(-0.85)	(-1.21)	(-0.51)	(-0.70)
Log_residence_income	0.028	0.028	0.013	0.013
	(1.27)	(2.00)**	(0.34)	(0.40)
Log_bank_saving	0.004	0.004	-0.005	-0.005
	(0.20)	(0.34)	(-0.20)	(-0.21)
Log_inflation	0.075	0.075	0.059	0.060
	(2.40)**	(2.47)**	(0.74)	(1.10)
Log_import	0.000	0.000	0.005	0.005
	(0.38)	(0.49)	(1.50)	(1.51)
Log_export	0.001	0.001	0.005	0.005
	(1.09)	(1.54)	(1.19)	(1.47)
Unemploymentrate	0.002	0.002	0.003	0.003
	(1.21)	(2.18)**	(0.62)	(0.98)
Log_gov_exp	0.006	0.006	-0.011	-0.011
	(0.74)	(1.02)	(-0.58)	(-0.68)
Log_num_state_firms	-0.009	-0.008	0.009	0.009
	(-1.82)*	(-2.56)**	(0.86)	(1.09)
Log_num_private_firms	-0.003	-0.003	0.014	0.014
	(-0.35)	(-0.70)	(0.61)	(0.71)
Log_num_employ_public	0.002	0.002	0.005	0.005
	(0.23)	(0.55)	(0.28)	(0.37)
Log_num_employ_private	-0.002	-0.002	-0.002	-0.002
	(-0.39)	(-0.70)	(-0.24)	(-0.25)
Constant	-0.404	-0.403	-0.331	-0.342
	(-1.19)	(-2.25)**	(-0.60)	(-0.75)
Observations	29,697	29,697	1,873	1,873
Number of id	511	511	224	224
FUND FE	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES
REGION FE	YES	YES	YES	YES
REGION CLUSTER	NO	YES	NO	YES
r2_o	0.145	0.145	0.194	0.194

Table 8: The Impact of Trust in Different Distribution Channels

This table reports the relationship between *trust-induced flows* and the disposition effect with three different distribution channels: bank channel, broker channel and direct channel. Models (1) to (2), (3) to (4), and (5) to (6) tabulates the impact of *trust-induced flows* on the disposition effect among the bank channel, brokerage channel, and online channel. Appendix A provides more detailed variable definition. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively. The sample period is from 2002 to 2011.

Dependent Variable = The Disposition Effect						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Bank Channel		Broker Channel		Direct Channel	
Trust Induced Flow	-0.049	-0.048	-0.092	-0.091	-0.092	-0.092
	(-2.59)***	(-2.56)**	(-4.37)***	(-4.29)***	(-2.84)***	(-2.84)***
Other Flow		0.001		0.001		-0.000
		(0.91)		(0.57)		(-0.28)
Log_GDP	0.001	0.001	0.007	0.007	0.008	0.008
	(0.34)	(0.41)	(1.45)	(1.44)	(1.36)	(1.36)
Log_pop	0.001	0.001	-0.008	-0.008	-0.007	-0.007
	(0.82)	(0.77)	(-1.52)	(-1.52)	(-1.27)	(-1.27)
Log_residence_income	0.004	0.003	0.006	0.006	-0.008	-0.008
	(1.00)	(0.97)	(0.51)	(0.51)	(-0.51)	(-0.51)
Log_bank_saving	0.000	0.000	0.009	0.009	-0.013	-0.013
	(0.20)	(0.19)	(0.89)	(0.89)	(-1.21)	(-1.21)
Log_inflation	0.010	0.010	0.181	0.181	0.002	0.002
	(0.33)	(0.32)	(2.22)**	(2.22)**	(0.04)	(0.05)
Log_import	0.000	0.000	0.000	0.000	0.001	0.001
	(0.13)	(0.15)	(0.24)	(0.23)	(0.75)	(0.76)
Log_export	-0.000	-0.000	0.002	0.002	-0.000	-0.000
	(-0.84)	(-0.89)	(1.71)*	(1.70)*	(-0.08)	(-0.07)
Unemploymentrate	0.001	0.001	0.001	0.001	0.003	0.003
	(1.33)	(1.34)	(0.91)	(0.91)	(1.45)	(1.45)
Log_gov_exp	0.002	0.002	0.004	0.004	0.019	0.019
	(0.95)	(0.96)	(0.53)	(0.52)	(2.79)***	(2.80)***
Log_num_state_firms	-0.003	-0.003	-0.003	-0.003	-0.010	-0.010
	(-1.77)*	(-1.74)*	(-0.41)	(-0.42)	(-2.62)***	(-2.63)***
Log_num_private_firms	0.000	0.000	-0.022	-0.022	-0.001	-0.001
	(0.13)	(0.08)	(-3.56)***	(-3.55)***	(-0.07)	(-0.08)
Log_num_employ_public	0.002	0.002	-0.006	-0.006	0.008	0.008
	(0.83)	(0.81)	(-0.88)	(-0.88)	(0.96)	(0.96)
Log_num_employ_private	-0.003	-0.003	0.010	0.010	-0.003	-0.003
	(-1.73)*	(-1.69)*	(1.85)*	(1.86)*	(-0.66)	(-0.66)
Constant	-0.069	-0.066	-0.915	-0.913	0.090	0.089
	(-0.41)	(-0.40)	(-2.48)**	(-2.48)**	(0.33)	(0.33)
Observations	11,441	11,441	10,451	10,451	9,869	9,869
Number of id	173	173	167	167	171	171
FUND FE	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES
REGION FE	YES	YES	YES	YES	YES	YES
REGION CLUSTER	YES	YES	YES	YES	YES	YES
r2_o	0.134	0.134	0.175	0.175	0.139	0.139

Figure 1: Social trust, fund flow, and the disposition effect.

Panel A illustrates a univariate version of Table 2. It plots the univariate relationship between trust and flow-performance sensitivity at the regional level. Specifically, for each region, we first estimate the time-series flow-performance sensitivity for each regional account and aggregate across all distribution channels to obtain the average flow-performance sensitivity of the region. We then plot social trust, using Zhang and Ke's (2002) measure, on the x-axis and the average flow-performance sensitivity of the regional account on the y-axis. Similarly, Panel B illustrates a univariate version of Table 3. It plots the relationship between the average *trust-induced flows* of a region (x-axis) and the average disposition effect of the region (y-axis), where *trust-induced flows* are estimated over the entire sample period.