Political Connection, Corruption, and Demand-Driven Stock Returns

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Abstract

I show that shifts in fund demand significantly impact stock returns. Using a reduced-form structural model and a characteristic-based demand asset pricing system, I investigate the price impact of firm-level political connections on stock returns through public fund demand, particularly after the 2012 anti-corruption campaign in China. Firstly, political connections have an insignificant direct effect on stock returns as an additional pricing factor but significantly and negatively affect stock returns through the fund demand channel, highlighting the importance of public fund demand. Meanwhile, the demand shifts in public funds significantly contribute to the decline in concurrent stock returns: public funds generally reduce holdings of stocks with higher political connections, especially those headquartered in provinces with elevated corruption indices, following the anti-corruption campaign announcement. By controlling for size and value factors that traditionally account for anomalies in Chinese stock returns, I reveal that non-fundamental demand shocks play a significant role not captured by political risk factors. This demand-based analysis introduces a novel perspective, distinct from conventional political risk literature that focuses on discount rate or cash flow-based analyses, and provides causal evidence for the decrease in stock returns during periods marked by unexpected political events.

Keywords: demand shifts, political connection, corruption, stock returns, public fund, institutional investor, demand elasticity

JEL Codes: G11, G12, G15, G18

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1 Introduction

Previous studies have identified financial intermediaries as both the marginal investors and the primary drivers of the pricing kernel in stock markets (Allen, 2001; Staikouras, 2003; Allen & Gale, 2004; Duffie, 2010; He & Krishnamurthy, 2013). Understanding the role of institutional investors is thus crucial for explaining asset pricing anomalies that previous models have failed to resolve. Significantly, latent demand, referring to unobserved stock characteristics, accounts for a major portion of the variance in cross-sectional stock returns (Koijen & Yogo, 2019). However, there is a gap in estimating the cross-sectional demand of institutions over time, particularly concerning non-fundamental political demand shocks. Given its status as the world's second-largest economy and the regional variations in corruption (Dong & Torgler, 2013), China presents an ideal setting for exploring politically related research questions. The recent, large-scale anti-corruption campaign in China, a significant political event, has triggered diverse market reactions, increased financial market volatilities, and led to lower stock prices (C. Lin et al., 2016; L. X. Liu et al., 2017; Griffin et al., 2021). Consequently, investigating political-driven demand shifts offers valuable insights into the behavior of institutions within a demand-based system, enriching our understanding of both developing and developed markets.

This paper aims to investigate the price impact of firm-level political connections through the channel of public fund demand. Past studies have shown that investors generally value political connections, even though politically connected firms tend to underperform (Fan et al., 2007). However, there should be heterogeneity among institutions in their demand for firms' political connections due to different preferences, beliefs, investment horizons, investment styles, or even regulations.

Understanding the demand of institutional investors in China is crucial for two main reasons: first, institutional investors are marginal investors, and their demand significantly affects the stock market; second, their heterogeneous demand for firm-level political connections means that estimating the price impact of political connections through the demand channel can provide valuable insights, especially during periods of higher political uncertainty.

This study focuses primarily on public funds because they provide detailed holding data on stocks, whereas other types of institutions only report their stock holdings if they are among the top ten shareholders or top ten negotiable shareholders, making the estimation less reliable. More specifically, I examine the influence of fund demand on stock returns in China, employing both a reduced-form structural model and a characteristic-based demand asset pricing approach. However, despite the limitations in data, the holding data of other types of institutions is necessary to meet the market clearing condition under the demand-based asset pricing system. Therefore, I will also apply the demand-based asset pricing model to estimate the price impacts from demand shifts of public funds, controlling for the demand of other institutions.

Firstly, the study seeks to understand the collective inclination of Chinese institutions towards politically connected firms. Although previous research, such as Fan et al. (2007), has noted the underperformance of politically connected firms, it remains uncertain whether institutional investors perceive such firms as higher political risks. My findings indicate that, with the exception of foreign institutions, domestic institutions progressively reduce their holdings in politically connected stocks over time, suggesting a diverse institutional appetite for political connections.

The research further explores whether these investment patterns shift following an exogenous event, specifically the 2012 anti-corruption campaign. Drawing on L. X. Liu et al. (2017), I regard a firm's board members with governmental or military backgrounds as indicators of political connections, with their number serving as a proxy for the firm's political ties. My analysis reveals that, post-campaign, public funds particularly demonstrate a marked aversion to stocks heavily linked to political figures, notably those in areas with high corruption and anti-corruption indices. I propose two potential explanations for this trend. On the one hand, the abrupt announcement of the anti-corruption initiative represents an unexpected non-fundamental demand shock, prompting fund managers to temporarily reduce their holdings in politically connected stocks as a precautionary measure. On the other, the extensive and top-down nature of the anti-corruption activities may constrain public funds' financing sources or inhibit their ability to invest in politically-connected stocks, particularly those at greater risk of investigation. Thus, this pattern offers an alternative explanation for the declining returns of politically connected stocks during 2012, driven by the unexpected demand shock affecting fund flows and portfolio decisions.

Having established that the demand shock has impacted fund managers' portfolio decisions, the subsequent analysis tests whether this politically-driven demand exerts real effects on stock returns. While other types of institutions exhibit no significant causal relationship, the politically-driven demand from public funds significantly impacts concurrent stock returns. Using controls for size and value factors in China, as suggested by J. Liu et al. (2019), although political connection is insignificant as a direct pricing factor, it can negatively and significantly impact stock returns through the fund demand channel. These results remain robust after adjusting for time, style, and fund fixed effects and are particularly pronounced for stocks headquartered in more corrupted provinces.

Future analyses will include variance decomposition during high political risk periods, price impact estimation under the demand based asset pricing system, and stock return predictability.

2 Related Literature

Over the past decades, there has been extensive academic interest in examining the stochastic behaviours of equilibrium asset prices in an exchange economy (Dumas, 1989; Detemple & Murthy, 1994, 1997; Basak & Cuoco, 1998). The "equity premium puzzle", which is a typical phenomenon among those stochastic behaviours, documents the inability in frictionless equilibrium models (Mehra & Prescott, 1985). A number of methods are used to resolve the equity premium puzzle. Some propose representative agent model, which reconciles agents with heterogeneous preferences (Dumas, 1989; Detemple & Murthy, 1994) and asset portfolio constraints with limited participation (Detemple & Murthy, 1997; Basak & Cuoco, 1998). However, the average household, which is typically used as a representative agent, lacks the necessary knowledge to invest in sophisticated assets or has limited participation in all financial markets (Adrian et al., 2014). Thus, despite the moral hazard friction, households usually invest through financial intermediaries, which play a significant role in asset allocation and capital flow (Allen, 2001; Staikouras, 2003; Allen & Gale, 2004; Duffie, 2010; He & Krishnamurthy, 2018).

Coval & Stafford (2007) and Edmans et al. (2012) demonstrate the relationship between fund flows and stock prices, showing how changes in fund inflows and outflows can lead to stock price fluctuations. The inelastic market hypothesis proposed by Gabaix & Koijen (2020, 2021), and further supported by Ben-David et al. (2021), suggests that markets do not perfectly absorb large trades, leading to significant price impacts from institutional demand.

Past well-established papers have typically featured CARA investors and partial equilibrium with rigorous assumptions and restrictions on investors' preference. These papers include the study for bonds (Greenwood & Hanson, 2013) and mortgage-backed securities (Gabaix et al., 2007) to confirm that the prices and risk premia could be influenced by both supply and demand side changes. Differently, demand-based asset pricing, which allows heterogeneity across different types of institutional investors, has become an innovative area of research in finance. As an accurate measure of investors' beliefs, the slopes of asset demand curves become a valid proxy of the optimal portfolio allocation in the equilibrium of the aggregate stock market, relaxing the strict assumptions of standard finance theory (Koijen & Yogo, 2019). Additionally, different sectors investigated by the pricing model play a vital role in the demand-based asset pricing system, where the behaviours of institutional investors are inconsistent (Koijen & Yogo, 2019). Under the demand-based asset pricing system, the dynamics of prices and capital flows, the role of various types of institutions and the effects of demand shocks have become easier to cross-sectionally analyze over time. More importantly, though extensive studies have evolved around models of the stochastic discount factor, such as empirical models with traded factors (Fama & French, 1993; Hou et al., 2015) and non-traded factors (Chen et al., 1986), the demand-based model matches investor holding data with asset prices and factors, shedding lights on portfolio choice applications (Koijen & Yogo, 2019).

Institutional investors are also found to respond to firm-level characteristics, adjusting their portfolios based on specific attributes of firms (Addoum & Kumar, 2016). Systematic changes in investor portfolios have been observed when the party in power changes, indicating a political dimension to investment strategies. Additionally, there is heterogeneity among institutional investors regarding their responses to climate risk (Koijen et al., 2023), showcasing the varied approaches and concerns among different types of institutional investors. Overall, these studies underscore the significant influence of institutional investors on stock prices and the various factors that drive their investment decisions.

3 Data

Institutional Holding data

I collect the institutional holding data from Institutional Investor - the China Stock Market and Accounting Research Database (CSMAR). Details on institutional shareholding, including names of institutional investors, codes of institutional investors, types of institutional investors, values of shareholding of institutional investors, volumes of institutional investors and percentages of institutional investors, are used for the main analysis. However, only long-position stock holdings are available in this dataset. CSMAR does not include information on holdings of bonds and cash, short-position stock holdings.

Stock Characteristics

The dataset comprises all publicly-listed companies on Mainland China's A-share market from June 1998 to March 2022. Monthly stock trading information, including prices, shares outstanding, and dividend payments, is sourced from the China Stock Market Series (CSMAR). Companies with incomplete data for share prices or shares outstanding are excluded.

Quarterly accounting data, such as operating working capital, net profit, shareholder's equity, total assets, and total liabilities, are obtained from the China Listed Firms Research Series - Financial Statement of CSMAR. To ensure that the accounting data was publicly available to investors at the time of trading, I use accounting data lagged by one quarter before merging it with the stock trading data.

Unlike the U.S. market, the China four-factor model (CH-4) effectively explains most of the anomalies reported in Chinese markets (J. Liu et al., 2019). Thus, I employ variables such as the price-to-earnings ratio[1], market capitalization, market beta, and turnover, which are key stock characteristics considered by Chinese institutions. Additionally, I retain only non-financial stocks for my empirical analysis and exclude financial firms due to their distinct accounting standards. However, financial stocks are utilized for constructing outside assets.

Political Connection and Corruption Index

Political Connection

Past studies state that a person is considered politically connected if he or she is currently or was previously working in the central government, local government, or the military (Fan et al., 2007; L. X. Liu et al., 2017). Using manually collected curriculum vitae (CV) of the board directors in Chinese publicly listed firms from financial reports, which are accessible via CSMAR and Sina Finance[2], I count the number of politically connected directors on the

[1]Building on the findings of J. Liu et al. (2019), the earnings-to-price ratio encompasses the book-to-market ratio in capturing the value effects in the Chinese market.

[2]https://finance.sina.com.cn/

board for each firm over time. Accordingly, the political sensitivity measured by political connections is defined[3].

However, one might argue that larger boards may have more political connections, suggesting that board size should also be considered when constructing proxies for political connections (C. J. Chen et al., 2011). Therefore, I also employ the proportion of politically connected board members as robustness tests.

Corruption Index

Following Dong & Torgler (2013), I create a province-level corruption index as the number of registered cases of corruption per 100,000 people each year, using data from the Procuratorial Yearbook of China.

Table 1 reports the summary statistics. The quarterly fund-level sample comprises 4,305,233 fund-month observations, with an average fund demand of 2.99%. For firm-level political connection, the average political connection across the 2,548,175 observations is 1.43. The province-level corruption index, covering the period from 2007 to 2018, has a mean of 2.42 and ranges from 0.99 to 6.10.

[Insert Table 1]

4 Research Questions

This section illustrates testable hypotheses about how institutional investors' investment patterns shift in relation to politically connected stocks following the 2012 anti-corruption campaign in China. This analysis uses both a reduced-form structural model and a characteristic-based demand asset pricing system. In particular, under the demand-based asset pricing system, the coefficients of characteristic-based demand for different types of investors could be estimated (Koijen & Yogo, 2019).

[3] Following L. X. Liu et al. (2017), the measure of political connection equals log (1 + number of politically connected board directors).

According to the inelastic market hypothesis, the aggregate stock market price elasticity of demand is small, indicating that unexpected demand shocks should have a large impact on stock prices (Gabaix & Koijen, 2021). Although comprehensive studies of political uncertainties and asset pricing in the Chinese stock market have been implemented, especially for the evaluations of stock returns, risk premium, and volatilities, to my best understanding, all the previous research is at the stock-level and conducts its analysis from the perspective of unsophisticated retail investors. There is a notable absence of insights from the standpoint of institutional investors. Consequently, I am proposing the following hypotheses:

Hypothesis 1: *Controlling for other stock characteristics, the political connection of a stock has a significant impact on institutional investors' demand.*

Hypothesis 2: *Controlling for other pricing factors, institutional investors' demand significantly explains realized stock returns.*

Hypothesis 3: *All else being equal, when political uncertainty is higher, institutional investors will show heterogeneous demand shifts for stocks with higher political connections.*

Hypothesis 4: *The shifts in institutional demand significantly impact realized stock returns.*

Hypothesis 5: *All else being equal, there should be a significant relationship between expected monthly returns and cross-sectional variation in stock returns in the long run.*

5 Empirical Methodology

Reduced Form Approach

On a quarterly basis, the first step is to observe the general trend between stock returns and institutional demand for all types of institutions. In the first stage:

$$demand_t = \beta_0 + \beta_1 political\,connection_{t-4} + \beta_2 controls + u_t \tag{1}$$

At the second stage, for different types of institutions i:

$$Return_t = \beta_0 + \beta_1 \hat{demand}_{i,t} + value_{t-1} + size_{t-1} + market\,beta_t + turnover_{t-1} + u_t \quad (2)$$

To measure the effect of an unexpected political event, such as the anti-corruption campaign, I then add a dummy variable equal to 1 if the records fall within the range from the last quarter of 2012 to the last quarter of 2013. The first stage becomes:

$$\begin{aligned} demand_t = \beta_0 + \beta_1 political\,connection_{t-4} + \beta_2 controls + \beta_3 dummy_{2012} + \\ \beta_4 dummy_{2012} * political\,connection_{t-4} + u_t \end{aligned} \quad (3)$$

At the second stage, for different types of institutions i:

$$Return_t = \beta_0 + \beta_1 \hat{demand}_{i,t} + value_{t-1} + size_{t-1} + market\,beta_t + turnover_{t-1} + u_t \quad (4)$$

Characteristics-Based Asset Demand System

According to Koijen & Yogo (2019), stock characteristics are sufficient for investors to construct their optimal investment portfolios. Thus, the portfolio weight on stock n is (for simplification, I drop time subscripts):

$$w_i(n) = \frac{\delta_i(n)}{1 + \sum_{m \in N_i} \delta_i(m)} \quad (5)$$

where

$$\delta_i(n) = exp(b_{0,i} + \beta_{0,i} me(n) + \beta_{1,i}^{'} x(n)) \epsilon_i(n). \quad (6)$$

and

- w_i: the portfolio weights in an investment universe $N_{i,t}$ that investor i chooses at date t to maximize expected log utility over terminal wealth.
- $b_{0,i}$: the intercept, refers to the investment in the outside asset.
- $\beta_{0,i}$: the price elasticity of demand.
- $me(n)$: the log market equity of stock n.
- $x(n)$: exogenous stock characteristics.
- $\beta_{1,i}$: the demand for stock characteristics.
- $\epsilon_i(n)$: the latent demand refers to the unobserved characteristics identified by econometricians.

6 Results - Reduced Form

6.1 Political Connection and Stock Returns

Figure 1 illustrates the cumulative return differences between stocks with the highest political connections and those with the lowest political connections. Specifically, stocks are sorted into five groups based on their political connections in the previous period. Group five consists of stocks with the highest lagged political connections, while Group one includes those with the lowest lagged political connections.

[Insert Figure 1]

Consistent with existing literature, the data shows that stocks with higher political connections generally underperform compared to those with lower political connections, indicating a negative relationship between stock-level political connections and stock returns. Notably, the underperformance of highly politically connected stocks becomes more pronounced around the last quarter of 2012, coinciding with the announcement of an anti-corruption campaign. This suggests that firm-level political connections are negatively linked to stock returns, and this negative relationship intensifies during periods of heightened political uncertainty.

If stocks with higher political connections typically underperform compared to those with lower political connections, this trend should be evident in regression results. Specifically, political connections should have a significant and negative impact on stock returns when considered as an additional pricing factor. Therefore, by accounting for earning price ratio, market capitalization, turnover ratio, and rolling beta, which are key characteristics of Chinese firms, lagged political connections are employed to price stock returns.

[Insert Table 2]

An OLS regression, controlling for firm fixed effects and time fixed effects, with robust standard errors clustered by industry and province, is employed. The results, shown in the first column of Table 2, indicate an insignificant relationship between lagged firm-level political connections and stock returns. This suggests that the pricing power of political connections has already been absorbed by other firm characteristics.

Given that this study focuses on the impact of public fund demand, a fund-level OLS regression is conducted to test the pricing power of fund demand. The results in the third column of Table 2 align with basic economic concepts, showing a positive and significant relationship between fund demand and concurrent stock returns. Additionally, this positive relationship is economically meaningful: a one standard deviation increase in fund demand leads to a 0.38% increase in concurrent stock returns.

6.2 Political Connection, Fund Demand, and Stock Returns

I further use political connection as an instrumental variable to evaluate the impact of fund demand on pricing stock returns. Table 3 shows the 2SLS results, controlling for other stock characteristics, time fixed effects, fund fixed effects, style fixed effects, and their interaction terms separately. Based on the results from the first stage, there is a significant and negative relationship between lagged political connection and fund demand, indicating that public funds prefer stocks with lower political connections over time. After confirming this significant relationship, I then regress stock returns on instrumented fund demand and other firm characteristics. According to the second stage, instrumented fund demand positively and significantly affects concurrent stock returns, confirming the importance of this demand channel. Combining the results from the first column of both stages, one can infer that a one standard deviation increase in political connection leads to a 0.16% decrease in stock returns. Similarly, a one standard deviation increase in political connection leads to a 0.07% decrease in stock returns based on the results from the second column. Consequently, although political connection is insignificant as a direct pricing factor, it can negatively and significantly impact stock returns through the fund demand channel, consistent with the underperformance trend of highly politically connected stocks shown in Figure 1 and past literature.

[Insert Table 3]

6.3 Effects of Anti-Corruption Campaign

Table 4 presents the effects of an unexpected exogenous political event: the announcement of the anti-corruption campaign in the last quarter of 2012. The period from the last quarter of 2012 to the last quarter of 2013 is treated as a dummy variable, representing a time of higher political uncertainty. The interaction term between political connection and this dummy variable captures the impact of the anti-corruption campaign.

[Insert Table 4]

Based on the regression results, the negative relationship between political connection and fund demand becomes stronger during the period of higher political uncertainty. This suggests that public funds demand fewer stocks with higher political connections during the anti-corruption period. Several reasons could explain this decreased fund demand. Firstly, fund managers might believe that temporarily reducing holdings of politically connected stocks is the best option due to higher political uncertainty during the anti-corruption period. Additionally, higher trading restrictions may have been applied to public funds during this time. For example, some funds might face increased governance and restrictions during the anti-corruption period, leading to decreased fund demand due to stricter trading constraints. Furthermore, all types of investors may become more conservative during periods of higher political uncertainty and redeem their investments in public funds, causing fund demand to decrease due to higher financial constraints.

In terms of economic impact, as shown by the first column of both stage one and stage two in Table 4, a one standard deviation increase in political connection leads to a 1.19% decrease in stock returns, indicating a much stronger negative impact on stock returns during periods of high political uncertainty. Overall, fund demand is a crucial channel through which firm-level political connection explains cross-sectional stock returns over time.

6.4 Anti-Corruption Campaign and Corruption Index

Unlike political connection, which is a firm-level characteristic rather than a political risk, the province-level corruption index can be considered a type of risk, especially during the anti-corruption campaign period. Therefore, it is interesting to examine the effects of different corruption indices, their interaction with political connection, and the subsequent impact on stock returns.

[Insert Table 5]

Firstly, based on the OLS results in the second column of Table 2, the corruption index generally has a positive effect on stock returns over time. However, based on Table 5, no significant relationship has been observed between the corruption index and fund demand, while the negative relationship between political connection and fund demand persists. Thus, compared to the corruption index, political connection is more critical when fund managers consider their portfolio allocations.

Regarding the interaction between the corruption index and political connection, the regression results in Table 5 indicate that the negative effect of political connection on stock returns becomes stronger when a firm is headquartered in a province with a higher corruption index. Additionally, the exogenous shock of the anti-corruption campaign leads to decreased returns for stocks with both higher political connection and a higher corruption index.

Estimation Results of Demand System

Following Koijen & Yogo (2019), I summarize the coefficients for characteristics-based demand (**??**) by GMM under moment condition (**??**). The cross-sectional mean of estimated coefficients for log market to book equity, log book equity, profitability, investment, dividends to book equity, market beta, and political connection are shown by institution type, weighted by the corresponding AUM. Moreover, because there are only limited observations on holdings of bank for the whole sample period, and on holdings of all institutions before 2005:2, I further adjust my sample from 2005:2 to 2022:1, in which institutional investors have higher stock market proportion. Consequently, the following sections show the cross-sectional mean of estimated coefficients for stock characteristics by eight institutions from 2005:2 to 2022:1, weighted by AUM.

Estimated Price Elasticity of Demand

According to Koijen & Yogo (2019), a lower coefficient on log market to book equity indicates a higher demand elasticity. In general, based on Figure 2, fund company, foreign institutions, financial investment, insurance company, social and government institutions tend to have stable demand elasticity over time. Nevertheless, among all the institutions, trust and non-financial institutions have both lower and volatile estimated coefficients over time, suggesting that they are having higher demand elasticity for log market to book equity over time.

Considering that there is no economic meaning for shares outstanding, the demand elasticity for market equity refers to their demand elasticity for stock price. For example, a -5 mean coefficient suggests that the institution will reduce its holding by 6% if the price increases by 1%[4]. Therefore, the elasticity of demand for trusts and non-financial institutions appears to be very sensitive to price changes over time, regardless of transaction costs. Consequently, it might be a good idea to investigate what these institutions are and the detailed holdings of their portfolios.

Trust Companies and Non-financial Institutions

For both trusts and non-financial institutions, I summarize the largest institution by AUM, the annual mean of AUM of the largest institution, the main types of shares in their portfolio, and the type of the largest institution.

As is shown in Table 10, in each year, all the largest trust companies are SOEs. More specifically, the trusts are either directly controlled by the SOEs or held by the big five banks. Interestingly, if a trust is directly controlled by the SOEs, such as China national petroleum corporation, Huaneng Corporation, and Shanghai International Trust Co., Ltd., it tends to have a small set of stocks in its investment portfolio. In contrast, if a trust is held by the big five banks, it normally has a well-diversified investment portfolio overtime. Different from western countries, China trust industry has been growing rapidly with difficulties in developing continuously and healthily, owing to the lack of core competence, exclusive business, and sufficient trust professionals[5]. Consistent with my results, the demand elasticity of trusts becomes less volatile in recent years because of the more regulated law and policy system. Also, given their risky nature and low chance of survivorship, the small and medium enterprises (SMEs) in China are faced with extreme difficulties in financing, leading trust companies serve as an alternative financing resources (Tao et al., 2022). It is plausible because the bank related trusts are having well-diversified portfolios overtime. Moreover,

[4]According to Koijen & Yogo (2019), the change of holding equals -(1 - the coefficient).

[5]http://www.xtxh.net/xtxh/english/index.jhtml

trust company seems to be a crucial channel for shadow banking, similar to the finding that bank-affiliated institutions play strategic roles in relationship banking, providing credit to clients to circumvent the credit tightening policy of the government (Chang et al., 2022).

Similar analysis applies to non-financial institutions, which typically refer to large SOEs. As is shown in Table 11, except for the last two years, all the largest non-financial institutions are SOEs. While the private institution only holds its own company's stock in the portfolio, the large SOEs are having a larger set of stocks in the related industries in their portfolio. Owing to its SOEs-dominated nature of the non-financial institution, a possible explanation for the volatile demand elasticity over time is: the non-financial institutions may adjust their portfolios for other purposes, for example, trading as a tool for government intervention.

Estimated Demand for Political Connection

Based on Figure 3, except for trusts and non-financial institutions, the remaining intuitions generally have stable demand for politically-connected stocks over time. If I zoom in the mean coefficients from 2010:2 to 2014:1, which refers to Period 4 of Table 7, I could further analyze if there is a decreasing trend in institutions' demand for stocks with political connections. Firstly, Period 4, after which the total market proportion of institutional investors has increased beyond 50%, serves as an ideal sample because it covers a period of high political uncertainty and exogenous unexpected political shocks, such as Bo's political scandal, leadership transmission, and announcement of anti-corruption campaign. As is shown in Figure 4, consistent with my hypothesis, institutional demand for stocks with political connections, excluding foreign institutions, shows a clear downward trend from 2012:3 to 2013:1. Moreover, the non-financial institutions and trusts contribute the most of this decreasing demand.

Considering that Figure 4 only shows the mean of estimated coefficients weighted by AUM, I further invoke a Jonckheere–Terpstra test to verify if a deceasing trend among all coefficients from 2012:3 to 2013:1 exists. Based on Table 9, the mean response score decreases as the date move forward, indicating there is a downward trend at the 1% significance level from 2012:3 to 2013:1.

I propose two possible explanations for this decreasing trend among Chinese institutions. On the one hand, Chinese institutions tilt their portfolio away from stocks with political connections because they believe the political risk is higher during this period. Thus, reducing holdings of politically connected stocks may protect institutions from higher political risk. On the other, Chinese institutions may feel that they are facing higher political uncertainty, and temporarily reducing their politically connected holdings becomes their best option at the time. Similar ideas shared by the foreign institutions. Before 2012, the foreign institutions generally has a negative demand for stocks with political connections, and they even decrease their demand from 2011:4 to 2012:3 owing to higher political uncertainty in 2012. Nevertheless, they tend to have a positive demand after the leadership transaction and announcement of anti-corruption campaign at 2012:4 while reduce their demand back to the original level after 2013:2. This adjustment might because foreign institutions initially regard the new leadership and announcement of anti-corruption campaign as a good signal to invest in politically-linked stocks, but they soon reduce their demand to the original level as the reality has failed to meet their expectations.

Therefore, except for foreign institutions, the Chinese institutional investors tilt their portfolio away from stocks with political connections, leading to lower aggregate demand and corresponding lower stock prices. This finding provides a new way to understand the share price decline in 2012, which past research has attributed to changes in discount rates and political risk in pricing (L. X. Liu et al., 2017).

Estimated Demand for Other Characteristics

In contrast to Koijen & Yogo (2019), who find positive mean coefficients of log book equity for all institutions, I observe negative mean coefficients for households, trusts and non-financial institutions while other institutions have positively stable coefficients over time in Figure 5.

Specifically, the coefficient of log book equity represents investors' demand for size. Thus, on average, non-financial institutions and trusts tilt their portfolio toward smaller stocks, supporting my explanations that the non-financial institutions may adjust their portfolios for other purposes and that trusts may serve as an alternative of financing for SMEs. In addition, household demand for size is both volatile and negative, which has become positive in recent years, suggesting households have recently preferred large stocks.

Different from Koijen & Yogo (2019), who find mean coefficients of profitability range from -1 to 2, Chinese institutional investors demand for profitability in larger magnitude. Except for certain periods, most institutions have positive demand for profitability over time, suggesting that company profitability is a key factor in investing.

Though different institutions are adjusting their demand for profit over time, the investment characteristic seems to be less important for institutional investors in China. As is shown in Figure 7, the magnitude of profitability is quite high while the magnitude of investment is extremely small. Thus, I can conclude that the investment factor is not important in the Chinese market, consistent with Q. Lin (2017), who states that for describing average returns, the investment factor is redundant.

Different from western countries, only a small sample of listed firms are paying cash dividends in China. This fact is owing to the unique institutional settings in China, which lead to conflicting effects for dividend payment: managers prefer to pay few or no dividends, controlling shareholders with nonnegotiable shares prefer cash dividends, while negotiable shareholders want capital gain rather than dividends (Huang et al., 2011). Therefore, limited to the few records of dividend payments, as is shown in Figure 8, I find relatively stable demand in small magnitude for dividends among all the institutions.

Lastly, following Koijen & Yogo (2019), I use the monthly rolling beta with a 60-month moving window for my beta estimation. In general, the demand for market beta of institutions tend to fall during recessions, such as 2008 financial crisis and 2015 Chinese stock market crash[6], suggesting that the demand for market risk is procyclical.

Figure 10 presents the cross-sectional standard deviation for log latent demand of different institutions, weighted by AUM. A higher standard deviation means more extreme portfolio weights tilted towards unobserved characteristics. Except for certain quarters, social and government institutions, foreign institutions, fund, insurance company, and financial investment tend to have fewer variations in latent demand. In contrast, trusts, non-financial institutions, and households have very large variation in latent demand over time. Again, trusts and non-financial institutions may have other motives that are not observable by stock characteristics when they adjust their portfolios.

Weak Instrument

A first-stage regression of log market equity on the instrumental variables and other stock characteristics is invoked to test the weak instrument issues in **??**, using the critical value given by Stock & Yogo (2005). For each quarter, such first-stage regression is employed for each institutional investor. Figure 11 shows the minimum first-stage t statistic on the instrumental variable of all institutions for each quarter, indicating that after 2004, all the first-stage t statistics are above the critical value of 4.05 to reject the null hypothesis of a weak instrument at the 5 significance level. This case is acceptable because there are only limited observations before 2004, and my research will focus on periods with more institutional investors. Also, an ideal scenario for the instrumental variable is to allow the variation of the investment universe across institutions, because the cross-sectional variation of the instrumental variable is mainly driven by such variation across institutions' investment universes. In Table 7, from 2006 to 2022, the median institution has only 1 stock in its investment universe and the 90th percentile institution has only 75 to 147 stocks, showing that institutions tend to have a small set of stocks in their investment universe. Thus, it is plausible to confirm the variation in the investment universe across institutions.

[6]For example, stated by Sornette et al. (2015).

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Tables

Table 1: Summary Statistics

	Obs	Mean	Std dev	Min	Max
Political Connection	2,548,175	1.43	0.64	0.00	3.66
Corruption Index	1,466,828	2.42	0.70	0.99	6.10
Size	4,305,233	10.21	1.26	5.30	12.77
Value	4,283,585	0.02	0.03	-0.99	0.33
Beta	4,500,627	1.01	0.60	-20.69	11.38
Turnover	4,305,233	0.27	0.28	0.00	3.82
Fund Demand (%)	4,305,233	2.99	0.32	-105.28	170.77

Table 2: Political Connections, Corruption Index, and Fund Demand as Pricing Factors

This table presents the results of OLS regressions, incorporating firm-level lagged political connections, the corruption index, and fund demand as additional pricing factors. The regressions control for common firm characteristics, including lagged size, price-earnings ratio, rolling beta, and turnover ratio. Definitions of these variables are provided in Appendix A. The models account for time effects, firm fixed effects, and style fixed effects. The t-statistics, calculated based on robust standard errors clustered by firm and province, or fund and province, are reported in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Return $_t$	(2) Return $_t$	(3) Return $_t$
Political Connection $_{t-1}$	0.11%		
	(0.82)		
Corruption Index $_{t-1}$		0.69%**	
		(2.09)	
Fund Demand $_t$			1.20%***
			(5.37)
Value $_{t-1}$	0.46***	0.66***	0.14***
	(16.38)	(15.30)	(21.75)
Size $_{t-1}$	-0.06***	-0.09***	-0.71%***
	(-31.62)	(-38.05)	(-7.46)
Turnover $_{t-1}$	-0.05***	-0.02***	-0.05%**
	(-24.97)	(-14.29)	(-9.46)
Beta $_{t-1}$	0.02%	0.12%	0.14%***
	(0.83)	(1.67)	(11.34)
Constant	0.58**	0.80***	0.11***
	(33.13)	(36.03)	(9.85)
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	
Style FE			Yes
Observations	81,356	56,377	4,149,634
Adjusted R^2 (%)	48.66	53.81	26.11

Table 3: Political Connection, Fund Demand and Realized Stock Returns

This table presents the results of two-stage least-squares (2SLS) regressions, using firm-level lagged political connection as the instrumental variable (IV). The regressions control for common firm characteristics, including lagged size, price-earnings ratio, rolling beta, and turnover ratio. Definitions of these variables are provided in Appendix A. The models account for time effects, fund investment style fixed effects, and their interaction terms. The t-statistics, calculated based on robust standard errors clustered by fund and province, are reported in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Stage 1		Stage 2	
	Demand $_t$	Demand $_t$	Return $_t$	Return $_t$
Demand $_t$ (Instrumented)			12.45**	3.28***
			(2.85)	(6.47)
Political Connection $_{t-1}$ (IV)	-0.05%**	-0.08%***		
	(-2.44)	(-6.56)		
Constant	0.34***	0.39***		
	(18.63)	(36.24)		
Mean of Demand $_t$ (Instrumented)			0.39	0.39
Std Dev of Demand $_t$ (Instrumented)			0.04	0.04
Controls $_{t-1}$	Yes	Yes	Yes	Yes
Time FE	Yes		Yes	
Style FE	Yes		Yes	
Time × Style FE		Yes		Yes
Time × Fund FE		Yes		Yes
Observations	2,458,668	2,452,895	2,446,707	2,440,909
Adjusted R^2 (%)	3.36	12.76		

Table 4: Difference in Differences: Effects from Anti-Corruption Campaign

This table shows the Difference-in-Differences (DID) results based on two-stage least-squares (2SLS) regressions, using firm-level lagged political connection and its interaction term with the anti-corruption dummy (Dummy_{2012}) as instrumental variables. The anti-corruption dummy refers to the year following the last quarter of 2012, which marks the announcement of the anti-corruption campaign. The regressions control for common firm characteristics, including lagged size, price-earnings ratio, rolling beta, and turnover ratio. Definitions of these variables can be found in Appendix A. The models account for time effects, fund investment style fixed effects, and their interaction terms. The t-statistics, calculated based on robust standard errors clustered by fund and province, are reported in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Stage 1		Stage 2	
	Demand $_t$	Demand $_t$	Return $_t$	Return $_t$
Demand $_t$ (Instrumented)			0.97**	1.97***
			(2.68)	(4.24)
Political Connection $_{t-1}$	-2.23%***	-1.82%***		
	(-10.27)	(-14.02)		
Political Connection $_{t-1}$ × Dummy $_{2012}$	-2.70%***	-2.36%***		
	(-11.52)	(-17.43)		
Constant	0.34***	0.39***		
	(18.95)	(37.66)		
Mean of Demand $_t$ (Instrumented)			0.39	0.39
Std Dev of Demand $_t$ (Instrumented)			0.04	0.04
Controls $_{t-1}$	Yes	Yes	Yes	Yes
Time FE	Yes		Yes	
Style FE	Yes		Yes	
Time × Style FE		Yes		Yes
Time × Fund FE		Yes		Yes
Observations	2,458,668	2,452,895	2,446,707	2,440,909
Adjusted R^2 (%)	3.40	12.79		

Table 5: Anti-Corruption Campaign and Corruption Index

This table shows the Difference-in-Differences (DID) results based on two-stage least-squares (2SLS) regressions, using firm-level lagged political connection, corruption index, and their interaction term with the anti-corruption dummy (Dummy_{2012}) as instrumental variables. The anti-corruption dummy refers to the year following the last quarter of 2012, which marks the announcement of the anti-corruption campaign. The regressions control for common firm characteristics, including lagged size, price-earnings ratio, rolling beta, and turnover ratio. Definitions of these variables can be found in Appendix A. The models account for time effects, fund investment style fixed effects, and their interaction terms. The t-statistics, calculated based on robust standard errors clustered by fund and province, are reported in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Stage 1		Stage 2	
	Demand $_t$	Demand $_t$	Return $_t$	Return $_t$
Demand $_t$ (Instrumented)			0.38***	0.33***
			(10.66)	(10.84)
Political Connection $_{t-1}$	-1.09%**	-0.56%**		
	(-1.91)	(-2.19)		
Corruption Index $_{t-1}$	0.07%	0.11%		
	(0.18)	(0.63)		
PC $_{t-1}$ × Corruption $_{t-1}$	0.07%	-0.17%***		
	(0.44)	(-3.41)		
Political Connection $_{t-1}$ × Dummy $_{2012}$	-3.90%***	-2.97%***		
	(-4.89)	(-6.20)		
Corruption Index $_{t-1}$ × Dummy $_{2012}$	0.07%	0.37%		
	(1.45)	(1.48)		
PC $_{t-1}$ × Corruption $_{t-1}$ × Dummy $_{2012}$	-0.75%***	-0.48%***		
	(-3.58)	(-3.49)		
Constant	0.54***	0.61***		
	(28.74)	(66.79)		
Mean of Demand $_t$ (Instrumented)			0.61	0.61
Std Dev of Demand $_t$ (Instrumented)			0.06	0.06
Controls $_{t-1}$	Yes	Yes	Yes	Yes
Time FE	Yes		Yes	
Style FE	Yes		Yes	
Time × Style FE		Yes		Yes
Time × Fund FE		Yes		Yes
Observations	1,303,725	1,293,254	1,303,121	1,292,625
Adjusted R^2 (%)	4.27	14.99		

Table 6: Persistence of The Investment Universe.

This table presents the percentage of stocks held in the current investment universe that were ever held in the previous 1 to 11 quarters. The pooled mean of all institutional investors over time is shown in each cell for given assets under management (AUM) percentile. The quarterly sample period ranges from 1998:2 to 2022:1.

	Previous Quarters										
AUM Decile	1	2	3	4	5	6	7	8	9	10	11
1	92	92	93	94	94	95	95	96	96	97	97
2	92	93	94	94	95	95	96	96	97	97	97
3	91	93	94	95	95	96	96	96	97	97	97
4	90	92	94	95	95	96	96	96	97	97	97
5	91	93	95	95	96	96	97	97	97	97	98
6	92	94	95	96	96	96	97	97	97	97	98
7	92	94	95	95	96	96	97	97	97	97	97
8	92	94	95	95	96	96	96	97	97	97	97
9	92	94	95	96	96	96	96	97	97	97	97
10	93	94	95	96	96	96	96	97	97	97	97

Table 7: Summary Statistics of Institutions

This table shows the time-series mean of the summary statistics in each period, based on the institutional holding data from CSMAR. The quarterly sample period ranges from 1998:2 to 2022:1. Period 1 refers to 1998:2-2002:1; Period 2 refers to 2002:2-2006:1; Period 3 refers to 2006:2-2010:1; Period 4 refers to 2010:2-2014:1; Period 5 refers to 2014:2-2018:1; Period 6 refers to 2018:2-2022:1

	Number of	**% of Market**	**AUM (000,000)**		**Number of Stocks Held**		**Number of Stocks in Investment Universe**	
Period	**Institutions**	**Held**	**Median**	**90th Percentile**	**Median**	**90th Percentile**	**Median**	**90th Percentile**
1	12	2	962	1,610	18	28	32	46
2	1,853	30	196	859	12	29	30	80
3	3,460	46	134	1,960	1	7	1	54
4	5,453	58	219	2,725	1	12	1	75
5	9,506	55	323	3,637	1	18	1	85
6	14,188	66	239	2,921	1	31	1	147

Table 8: Summary Statistics of Firm Characteristics

This table shows the summary statistics of the stock characteristics for all the investors. Consistent with my estimation period, the quarterly sample period ranges from 2005:2 to 2022:1.

	Obs	**Mean**	**Std dev**	**Min**	**25th**	**Median**	**75th**	**Max**
LNme	5,511,421	8.226	0.887	-1.201	7.609	8.215	8.802	18.705
LNbe	5,511,421	8.633	1.589	-2.328	7.487	8.461	9.561	14.183
Profit	5,523,657	0.073	1.189	-32.216	0.035	0.065	0.106	16.814
Investment	4,840,035	0.192	0.002	-0.134	0.057	0.142	0.262	0.645
Political	4,725,446	1.295	0.654	0.000	0.693	1.386	1.792	3.664
Beta	4,662,534	1.065	0.443	0.241	0.801	1.046	1.303	2.198
Dividend	4,528,264	0.000	0.000	0.000	0.000	0.000	0.000	0.005
Leverage	5,528,380	0.398	0.206	0.025	0.228	0.391	0.552	0.923
Liquidity	5,335,329	26.680	25.204	0.026	9.723	17.760	34.537	153.797

Table 9: Jonckheere–Terpstra Test for Trend

This table shows the results of a Jonckheere–Terpstra test. All the estimated coefficients are assigned into 3 groups: 2012:3, 2012:4 and 2013:1. The corresponding observations, mean response score, and standard errors are shown in the table. $*, **$, and $***$ denote statistical significance at the 10%, 5%, and 1% level, respectively.

Date	**Mean response score**	**Number of observations**	**Std. err.**
2012:3	0.088***	6,383	39.558
2012:4	0.033***	53,695	39.558
2013:1	0.009***	6,587	39.558

Table 10: Annual Largest Trust

This table presents the annual largest trust company in terms of AUM from 2006 to 2022. The name of the largest trust company, its mean AUM in each year, and the type of the institution (SOE or non-SOE) are shown in Panel A; In Panel B, I include main types of shares in the portfolio of the example largest trust company. Specifically, CNPC refers to China national petroleum corporation, one of the largest SOEs in China.

Panel A

Year	Name	Mean AUM (in millions)	SOE
2006	Shanghai International Trust Investment Company	6,448	Yes
2007	Shanghai International Trust Co., Ltd.	16,929	Yes
2008	Shanghai International Trust Co., Ltd.	8,191	Yes
2009	Shanghai International Trust Co., Ltd.	39,610	Yes
2010	Shanghai International Trust Co., Ltd.	13,090	Yes
2011	Shanghai International Trust Co., Ltd.	11,170	Yes
2012	Shanghai International Trust Co., Ltd.	9,840	Yes
2013	Shandong International Trust Investment Company	11,721	Yes
2014	Shandong International Trust Investment Company	13,464	Yes
2015	Shenzhen International Trust Investment Co., Ltd.	42,888	Yes
2016	Shenzhen International Trust Investment Co., Ltd.	34,088	Yes
2017	CNPC - China Securities - Special Account	30,904	Yes
2018	CNPC - China Securities - Special Account	30,302	Yes
2019	Dacheng Fund - Agricultural Bank of China	31,557	Yes
2020	Dacheng Fund - Agricultural Bank of China	28,229	Yes
2021	ChinaAMC - Agricultural Bank of China	38,476	Yes
2022	Dacheng Fund - Agricultural Bank of China	24,266	Yes

Panel B

Trust Name	Type of Stocks in Portfolio
CNPC - China Securities - Special Account	Oil and Gas Extraction
Shanghai International Trust Co., Ltd.	Automobile Manufacturing
	Real Estate Industry
	Retailing
	Textile Industry
	Coal Mining and Processing
ChinaAMC - Agricultural Bank of China	Civil Engineering Construction
	Ancillary Activities for Mining
	Railroad Transport
	Medicine Manufacturing
	Wholesale

Table 11: Annual Largest Non-financial Institutions

This table presents the annual largest non-financial institutions in terms of AUM from 2006 to 2022. The name of the largest non-financial institution, its mean AUM in each year, and the type of the institution (SOE or non-SOE) are shown in Panel A; In Panel B, I include main types of shares in the portfolio of the example largest non-financial institution. Specifically, Sinopec Group refers to China Petroleum Chemical Corporation, one of the largest SOEs in China.

Panel A

Year	Name	Mean AUM (in millions)	SOE
2006	Sinopec Group	530,364	Yes
2007	China National Petroleum Corporation	1,958,618	Yes
2008	China National Petroleum Corporation	1,063,512	Yes
2009	China National Petroleum Corporation	1,380,482	Yes
2010	China National Petroleum Corporation	972,268	Yes
2011	China National Petroleum Corporation	1,677,179	Yes
2012	China National Petroleum Corporation	1,447,711	Yes
2013	China National Petroleum Corporation	1,261,656	Yes
2014	China National Petroleum Corporation	1,311,139	Yes
2015	China National Petroleum Corporation	1,606,713	Yes
2016	China National Petroleum Corporation	1,208,468	Yes
2017	China National Petroleum Corporation	1,379,241	Yes
2018	China National Petroleum Corporation	1,266,072	Yes
2019	Jizhong Energy Group Co., Ltd.	2,722,360	Yes
2020	China National Petroleum Corporation	1,475,772	Yes
2021	China National Petroleum Corporation	1,628,837	Yes
2022	China National Petroleum Corporation	882,696	Yes

Panel B

Trust Name	Type of Stocks in Portfolio
Sinopec Group	Water Transportation
	Oil and Gas Extraction
China National Petroleum Corporation	Water Transportation
	Ferrous Metal Smelting and Extruding
	Oil and Gas Extraction

Figures

Figure 1: Cumulative Return Difference

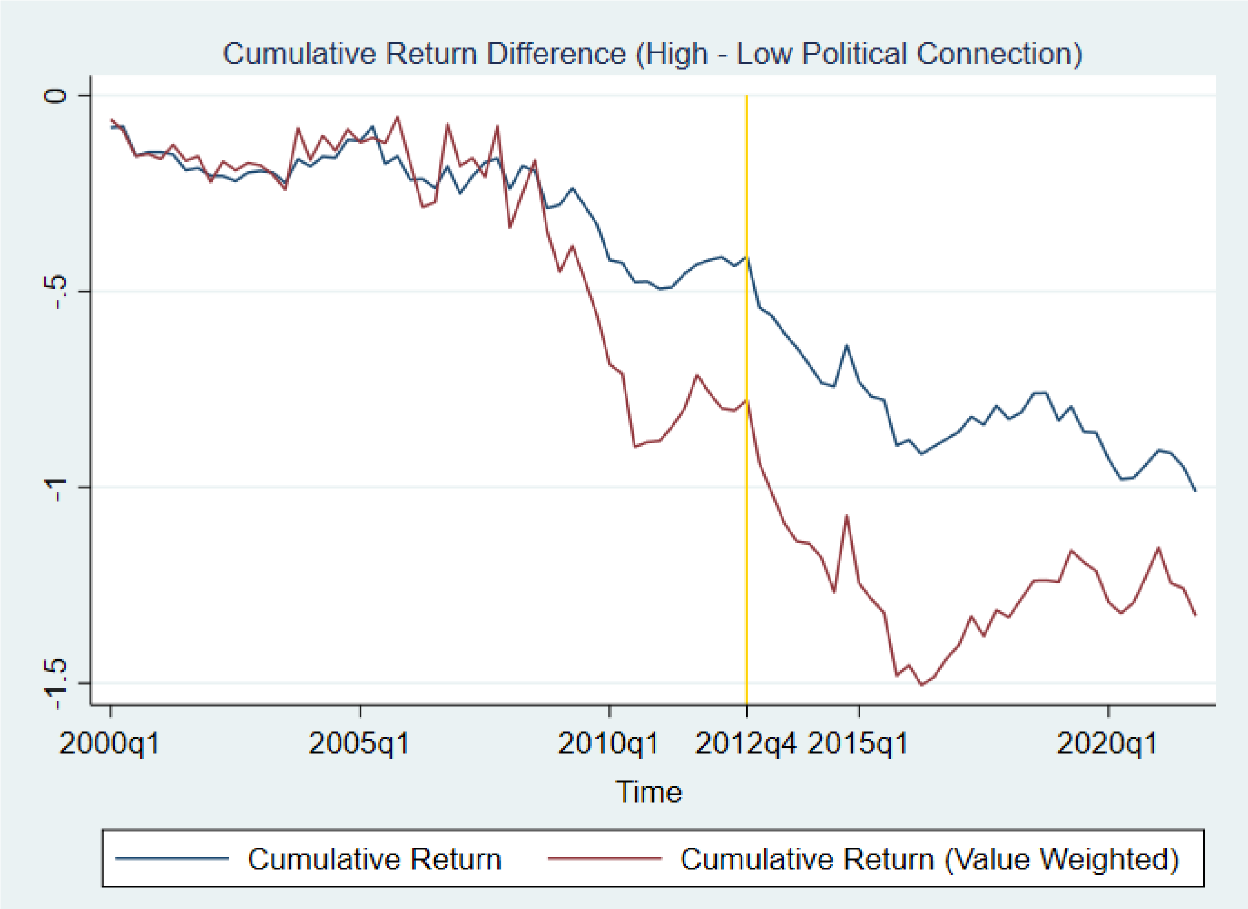


Figure 2: Coefficients on Log Market to Book Equity

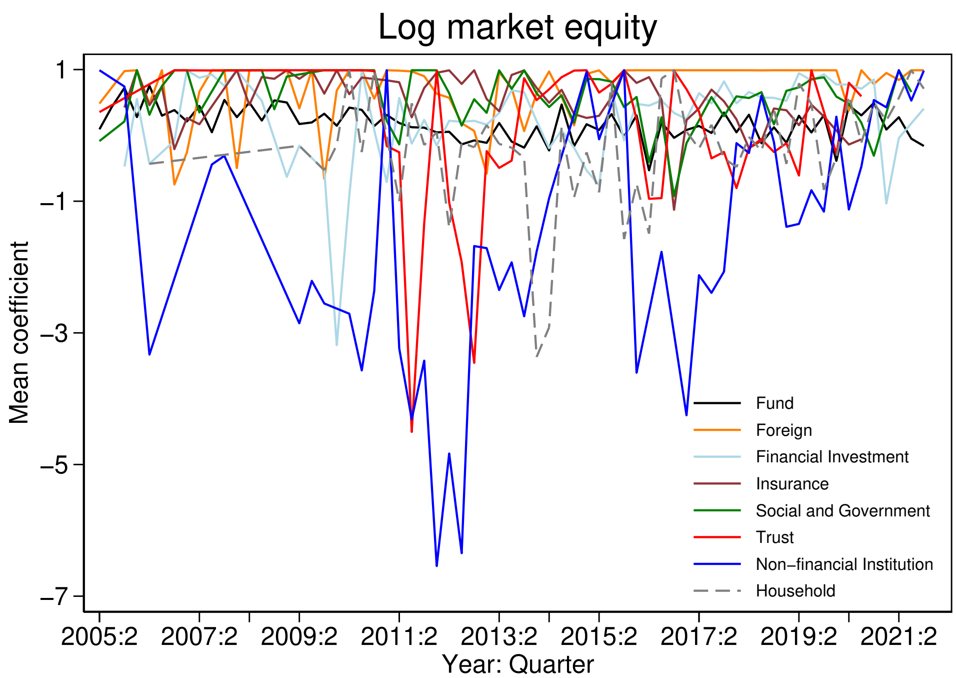


Figure 3: Coefficients on Political Connection

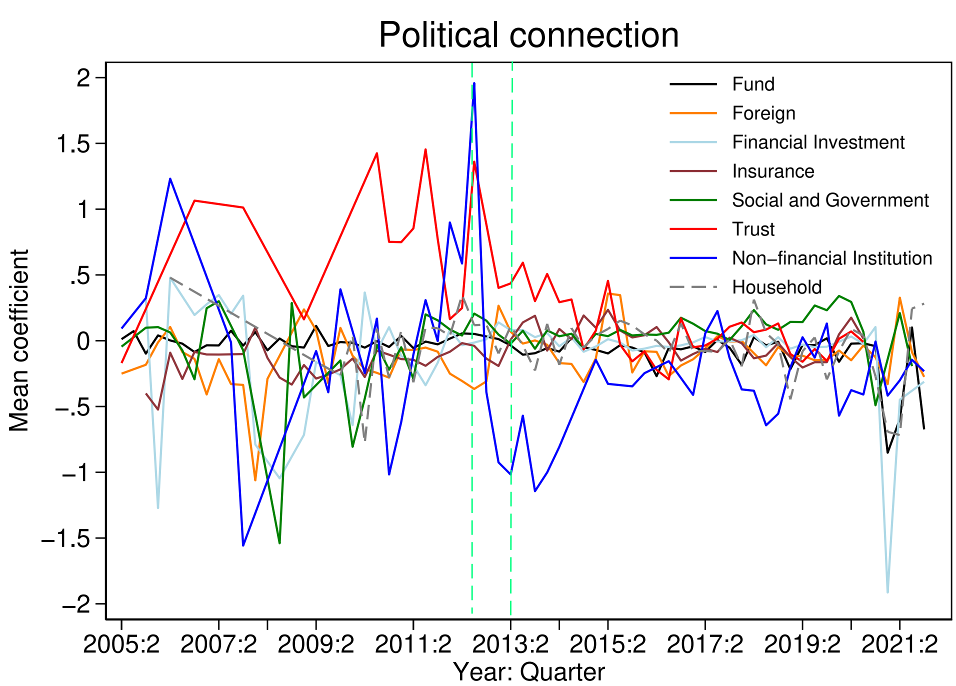


Figure 4: Coefficients on Political Connection - Sample

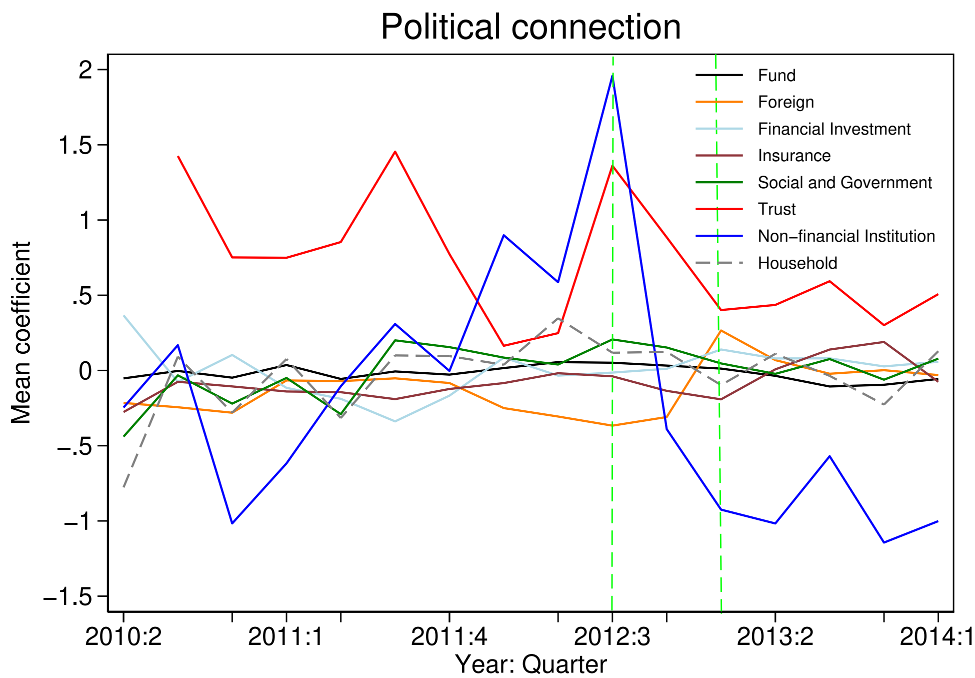


Figure 5: Coefficients on Log Book Equity

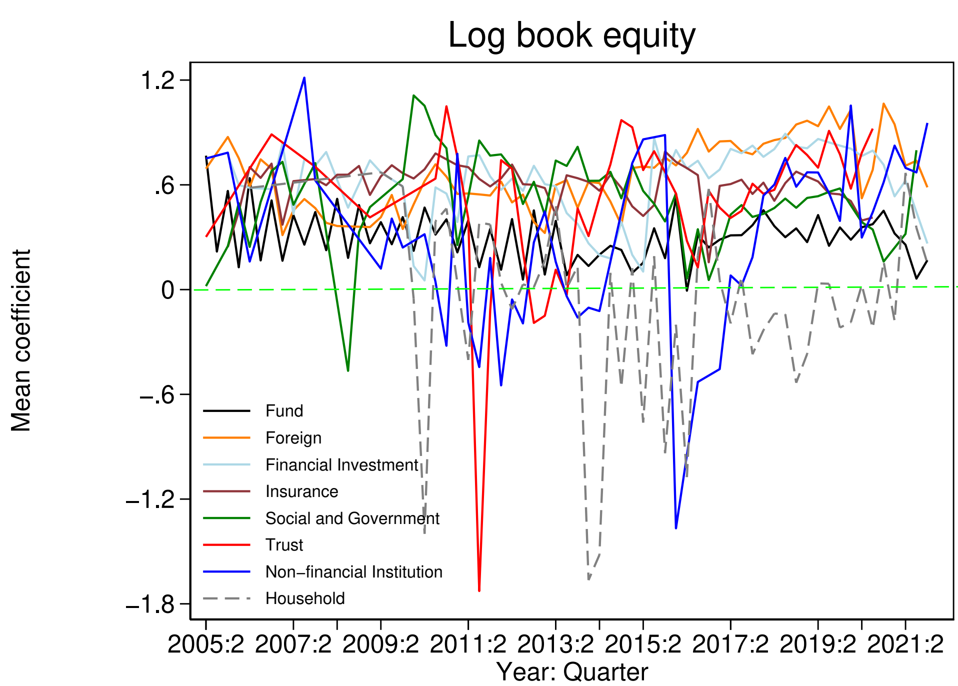


Figure 6: Coefficients on Profitability

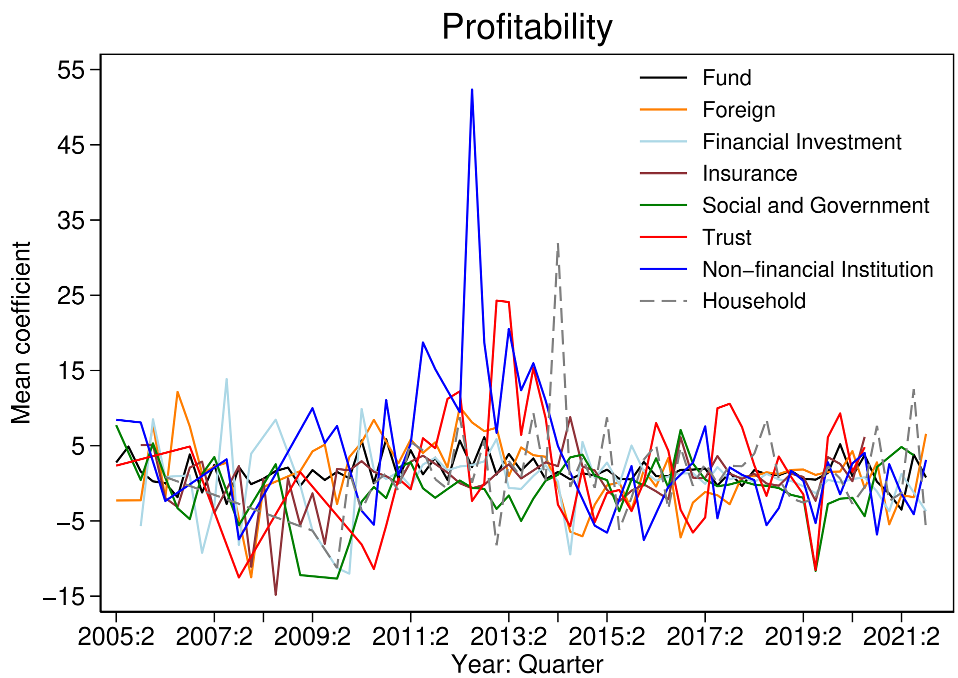


Figure 7: Coefficients on Investment

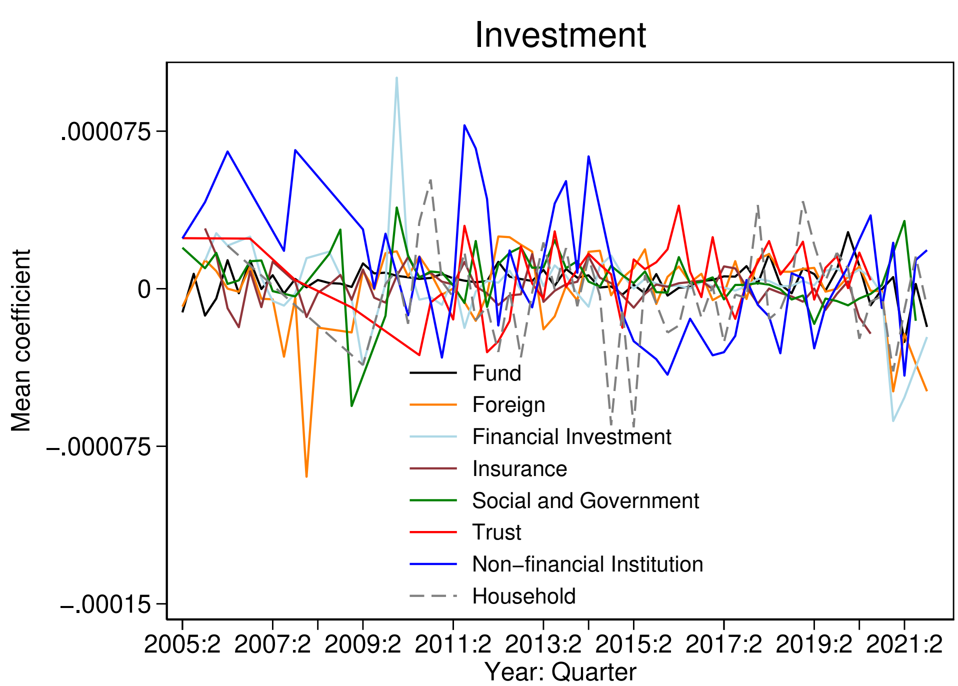


Figure 8: Coefficients on Dividend to Book Equity

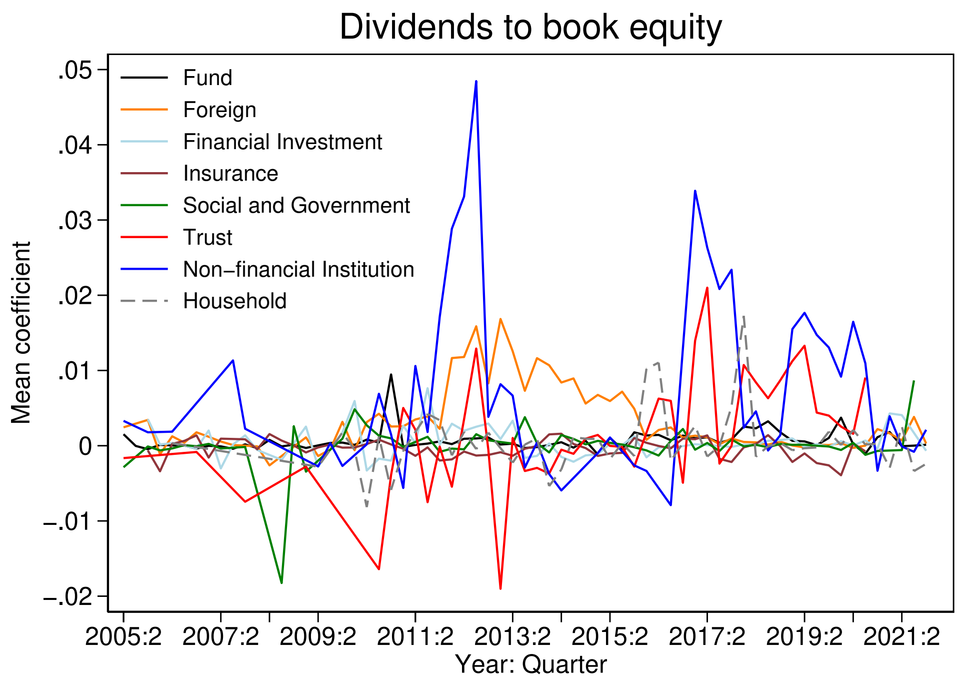


Figure 9: Coefficients on Market Beta

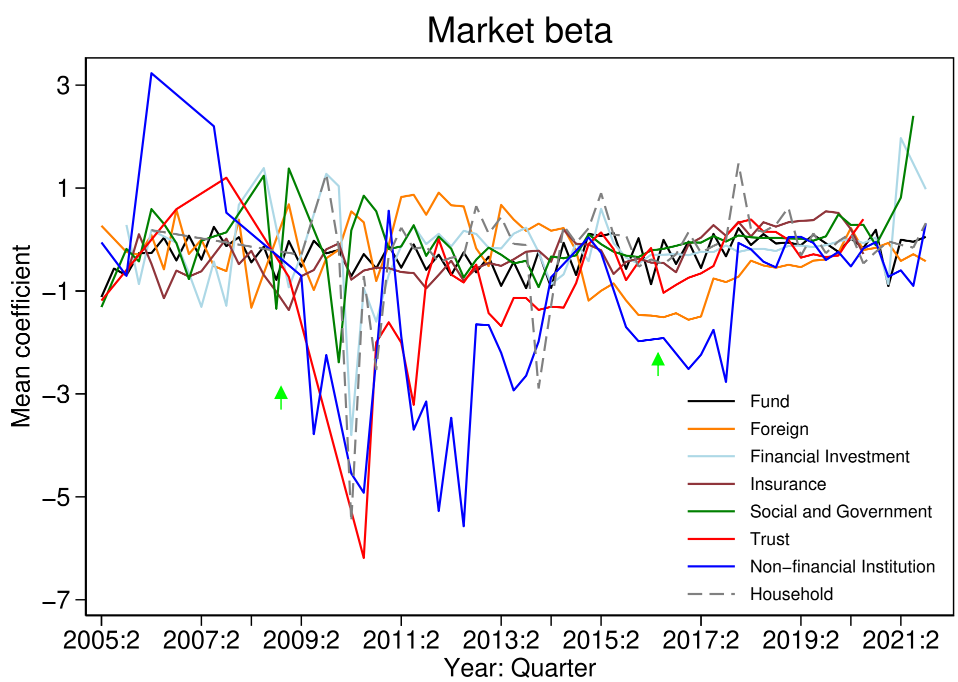


Figure 10: Standard Deviation of Latent Demand

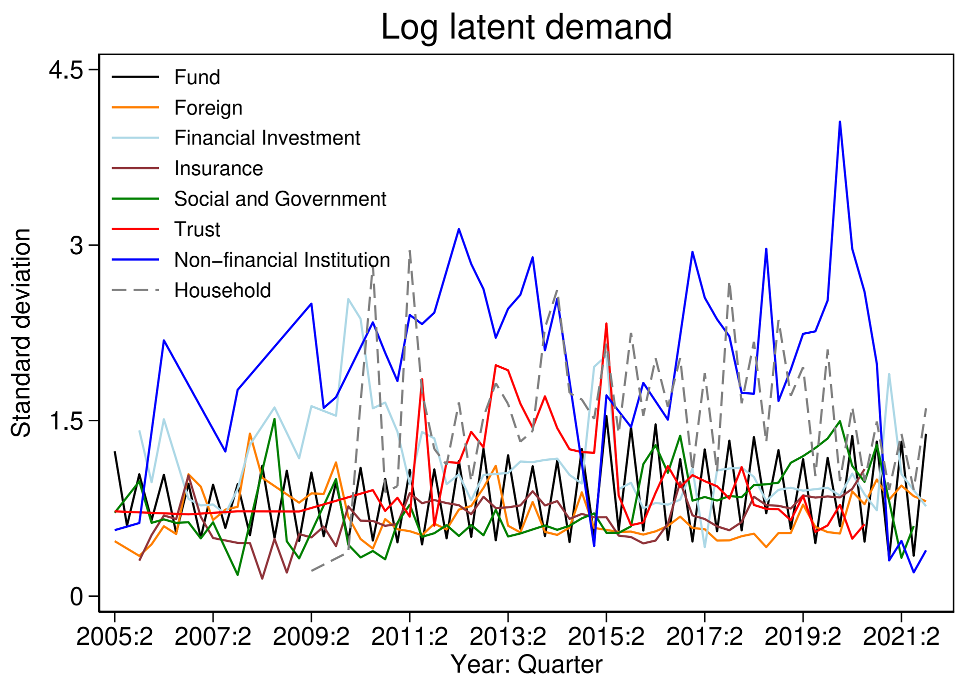
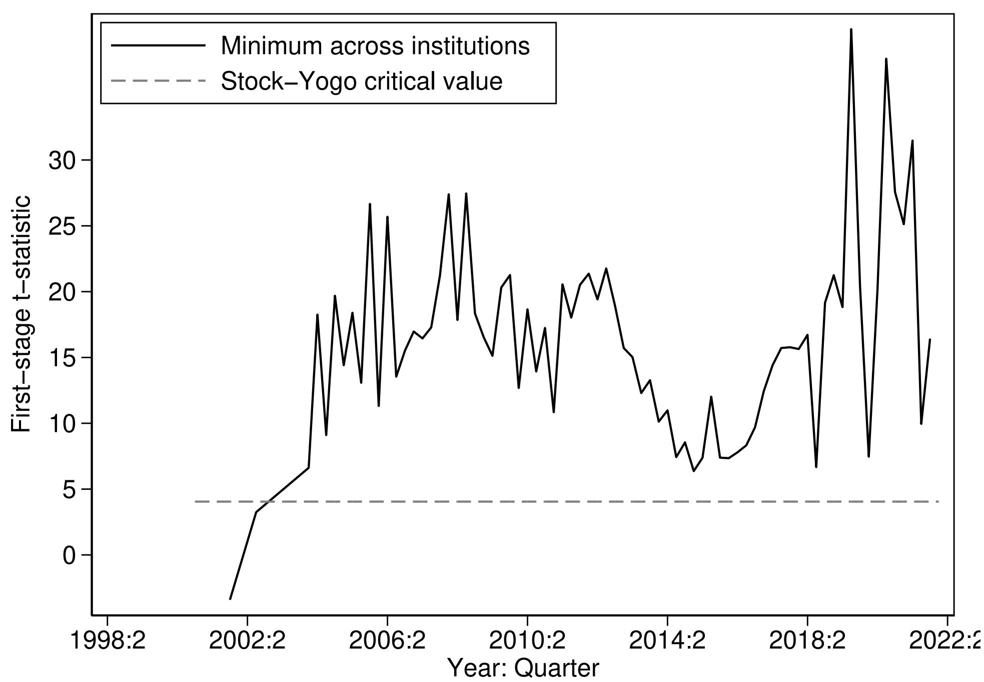


Figure 11: First-stage t statistic on the instrumental variable for log market equity



Appendix A

Table 12: Variable Definitions

Definition of Variables	
Variable	Definitions
Size	The logarithm of (stock price × stock shareholding)
Value	The ratio of net income to market capitalization
Beta	The monthly rolling market beta using a 60-month moving window
Turnover	The ratio of share trading volume divided by its total shares outstanding
Political Connection	The logarithm of (1 + number of politically connected board directors)
Corruption Index	The number of registered cases of corruption per 100,000 people annually in each province
Fund Demand	The ratio of the difference in shares held for a stock to the stock's lagged total shares outstanding
Dummy 2012	The year following the last quarter of 2012 - announcement of the anti-corruption campaign

Table 13: Corruption, Fund Demand and Realized Stock Returns

This table presents the results of two-stage least-squares (2SLS) regressions, using corruption index as the instrumental variable (IV). The regressions control for common firm characteristics, including lagged size, price-earnings ratio, rolling beta, and turnover ratio. Variable definitions can be found in Appendix A. The models account for time effects, fund investment style fixed effects, and their interaction terms. The t-statistics, calculated based on robust standard errors clustered by fund and province, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Stage 1		Stage 2	
	Demand $_t$	Demand $_t$	Return $_t$	Return $_t$
Demand $_t$ (Instrumented)			0.34	0.37**
			(1.62)	(2.33)
Corruption Index $_{t-1}$ (IV)	-0.33%***	-0.35%***		
	(-3.92)	(-4.81)		
Constant	0.56***	0.63***		
	(27.57)	(63.99)		
Mean of Demand $_t$ (Instrumented)			0.62	0.62
Std Dev of Demand $_t$ (Instrumented)			0.06	0.06
Controls $_{t-1}$	Yes	Yes	Yes	Yes
Time FE	Yes		Yes	
Style FE	Yes		Yes	
Time × Style FE		Yes		Yes
Time × Fund FE		Yes		Yes
Observations	1,321,033	1,310,460	1,320,459	1,309,862
Adjusted R^2 (%)	4.12	14.56		

Table 14: Difference in Differences: Anti-Corruption Campaign and Corruption

This table shows the Difference-in-Differences (DID) results based on two-stage least-squares (2SLS) regressions, using corruption index and its interaction term with the anti-corruption dummy (Dummy_{2012}) as instrumental variables. The anti-corruption dummy refers to a year following the last quarter of 2012, which marks the announcement of the anti-corruption campaign. The regressions control for common firm characteristics, including lagged size, earnings-price ratio, rolling beta, and turnover ratio. Variable definitions can be found in Appendix A. The models account for time effects, fund investment style fixed effects, and their interaction terms. The t-statistics, calculated based on robust standard errors clustered by fund and province, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Stage 1		Stage 2	
	Demand $_t$	Demand $_t$	Return $_t$	Return $_t$
Demand $_t$ (Instrumented)			0.37***	0.38***
			(3.56)	(4.04)
Corruption Index $_{t-1}$	0.16%	0.03%		
	(0.85)	(0.80)		
Corruption Index $_{t-1}$ × Dummy $_{2012}$	-0.64%***	-0.50%***		
	(-3.58)	(-12.13)		
Constant	0.56***	0.63***		
	(27.28)	(63.45)		
Mean of Demand $_t$ (Instrumented)			0.62	0.62
Std Dev of Demand $_t$ (Instrumented)			0.06	0.06
Controls $_{t-1}$	Yes	Yes	Yes	Yes
Time FE	Yes		Yes	
Style FE	Yes		Yes	
Time × Style FE		Yes		Yes
Time × Fund FE		Yes		Yes
Observations	1,321,033	1,310,460	1,320,459	1,309,862
Adjusted R^2 (%)	4.12	12.79		

Table 15: Variable Descriptions.

This table presents the definitions of variables invoked by this paper. The stock trading data, the accounting data, and the institutional holding data are collected from CSMAR in the period of 1998:6 to 2022:3. For the construction of stock characteristics, to reduce the impact of outliers, I winsorize investment, profitability, and market beta at the 2.5th and 97.5th percentiles. I winsorize dividends to book equity at the 97.5th percentile. I group institutional investors into eight types.

Category of Institutional Investors	
Type	**Institutions**
Fund	Fund Company, Security Investment Fund Fund Account Wealth Management, Public Welfare Fund
Foreign	QFII Shareholding (Qualified Foreign Institutional Investor) Other Overseas Institution
Financial Investment	Securities Brokerage Shareholding, Venture Capital Company Financial Asset Management Company, Futures Company Securities Investment Consulting Company
Insurance	Insurance Company, Insurance investment Portfolio
Social and Government	Social Security Fund Shareholding Government Institution/Public Institution
Trust	Trust Company, Trust Asset Management Plan
Bank	Bank
Other Institution	Other Non-Financial Institution
Stock Characteristics	
Variable	**Definitions**
Log market equity	The logarithm of (stock price $*$ stock shareholding)
Log book equity	The logarithm of shareholder's equity
Profitability	The ratio of operating profits to book equity
Investment	The logarithm of annual growth rate in total assets
Dividend to book equity	The ratio of annual dividends per share to book equity
Market beta	The monthly rolling beta using a 60-month moving window
Political connection	The logarithm of (1 + number of politically connected board directors)
Leverage	The ratio of total liabilities to total assets
Liquidity	The ratio of traded shares to total shares outstanding

Table 16: Summary Statistics of Institutions by Type

This table shows the time-series mean of the summary statistics in each period, based on the institutional holding data by institution type from CSMAR. The quarterly sample period ranges from 1998:2 to 2022:1. Period 1 refers to 1998:2-2002:1; Period 2 refers to 2002:2-2006:1; Period 3 refers to 2006:2-2010:1; Period 4 refers to 2010:2-2014:1; Period 5 refers to 2014:2-2018:1; Period 6 refers to 2018:2-2022:1

	Number of	**% of Market**	**AUM (000,000)**		**Number of Stocks Held**		**Number of Stocks in Investment Universe**	
Period	**Institutions**	**Held**	**Median**	**90th Percentile**	**Median**	**90th Percentile**	**Median**	**90th Percentile**
Panel A: Fund								
1	12	2	963	1,610	18	28	32	46
2	97	12	348	1,188	21	48	61	175
3	238	10	1,359	4,959	15	43	77	172
4	434	15	397	2,811	15	49	90	234
5	1,447	6	157	1,296	12	50	51	229
6	2,852	5	122	1,193	18	58	68	280
Panel B: Foreign								
2	139	6	92	723	1	7	1	10
3	165	13	201	1,597	1	7	1	27
4	232	11	262	2,201	1	4	1	17
5	285	5	471	3,381	1	4	1	13
6	425	13	593	6,452	1	2	1	6
Panel C: Financial Investment								
2	434	5	63	455	1	6	2	16
3	680	8	101	856	1	3	1	8
4	1,514	6	155	1,440	1	3	1	7
5	2,992	10	304	2,525	1	2	1	4
6	5,352	15	211	1,879	1	2	1	2
Panel D: Insurance								
2	10	0	32	274	1	5	1	7
3	26	1	75	2,629	2	14	8	59
4	43	0	122	2,443	3	19	10	72
5	73	1	450	3,015	2	15	8	61
6	87	0	499	3,503	2	9	5	40
Panel E: Social and Government								
2	94	1	243	860	5	13	10	28
3	102	4	201	1,712	1	8	2	40
4	142	2	266	3,824	1	10	1	33
5	146	3	596	4,062	1	21	1	82
6	173	0	460	4,954	1	14	2	62
Panel F: Trust								
2	60	0	48	290	2	6	3	17
3	67	0	39	611	1	4	3	10
4	241	0	59	456	2	5	4	14
5	1,193	1	157	697	1	3	1	9
6	682	1	138	739	1	2	1	6
Panel G: Bank								
2	20	0	58	213	1	4	1	5
3	22	0	75	657	1	4	1	9
4	24	0	79	878	1	3	1	5
5	16	0	122	752	1	2	1	4
6	58	0	201	1,222	1	2	1	2
Panel H: Non-Financial Institution								
2	1,799	6	56	668	1	2	1	3
3	2,160	10	126	1,781	1	2	1	3
4	2,823	23	308	3,838	1	2	1	2
5	3,354	29	801	5,273	1	2	1	2
6	4,560	32	510	6,291	1	2	1	2