Why corruption matters? Evidence from the anti-corruption campaign*

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July, 2020

Abstract

We study the effectiveness of the anti-corruption campaign by the Chinese government. We conduct a multiple-stage investigation considering, step-by step, all provinces of mainland China. We isolate the systematic and idiosyncratic component of the firms' total risk, and find that corruption is mostly associated to systematic risk. Initially, systematic risk increases because the local political instability induced by the campaign spills over the rest of the country. However, despite an initial negative reaction, as the investigation goes on, systematic risk decreases. We provide evidence that a top-down anti-corruption campaign combined with a high-state enforcement holds major implications in fighting corruption and reducing systematic risk.

JEL Classification Numbers: C22, G14, G17.

*We are grateful for comments from Robert F. Engle and seminar participants at HSBC Business School, Peking University, Fourth Annual Volatility Institute (VINS) Conference. We thank Giampiero M. Gallo for sharing the codes, The views expressed in this paper are those of the authors and do not necessarily reflect the views of the China International Capital Corporation Limited, Bank of Italy or of the Eurosystem. All remaining errors are our own. *Corresponding author*: Domenico Tarzia. Tel: +86-755-2603-3375. Email: *dtarzia@phbs.pku.edu.cn*.

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Keywords: Anti-corruption, Systematic risk, Idiosyncratic risk, Volatility spillovers, Top-down approach.

1 Introduction

Corruption is commonly defined as "abuse of entrusted power for private gain" by Transparency international. At the macro level, existing literature agrees on corruption being a key component in destroying value for the society, for by slowing down economic development (Shleifer and Vishny (1993)), especially in those countries with weak control of central government. On the other side, economic development could reduce corruption to some extent, and some specific countries might be more prone to severe corruption problems because of their social norms. Treisman (2000) shows that countries with different historical background and different levels of development face different degrees of corruption. Aidt, Dutta, and Sena (2008) define two different governance regimes, depending on the quality of political institutions, concluding that high quality political institutions are negatively affected by corruption in terms of growth. Spector (2016) shows how an anti-corruption campaign can achieve social, political and economic benefits. At the firm level, empirical findings are more controversial, since there is no unanimous agreement on the influence. Fisman and Svensson (2007) find evidence that an increasing bribery rate could lead to reduction in firm growth, and more surprisingly, that the effect of bribery is almost three times greater than that of taxation. Karpoff, Lee, and Martin (2008) show how, while penalties imposed on firms through the legal system appear to be marginal, the penalties imposed by the market are quite significant. Cheung, Rau, and Stouraitis (2012) show how firms benefit by paying bribes, and how firm performance, the rank of the politicians bribed, and country characteristics affect the significance of the bribes and the benefits obtained. Huang and Rice (2012) find that firms' increased networking and openness tend to occur contemporaneously with greater bribery and corruption. Mutlu (2014) focuses on the relationship between bribery and firm performance in different institutional environments, finding how bribery could boost firm performance, especially in the underdeveloped political environments.

In 2013, China initiated a nation-wide broad-ranged investigation on corruption, targeting local governments, state-owned enterprises (SOEs), state-run universities, etc. From

May 2013, to March 2017, the Central Commission for Discipline Inspection (CCDI) performed twelve different batches of investigation. The twelve batches can be grouped into three rounds: first four batches targeting the provincial governments of all 31 provinces of mainland China (macro level); second four batches targeting state-owned enterprises and corporate groups (micro level); and the third four batches targeting state-run universities, government departments and commissions.[1]

[Table 1 about here.]

Table 1 summarizes the basic information of the first rounds of the campaign, including the announcement and ending date of the investigation for each province. The official investigation decisions are announced directly by CCDI, and information on successive development of the investigations are disclosed to public on its website. Figure 1 shows how the batches of investigation are not geographically-clustered.

[Figure 1 about here.]

We make use of the nationwide anti-corruption movement in China as the natural experiment to see the effects of such extensive and multiple-step policy on the entire economic system. Step by step, indeed, the investigation concerns the entire country itself. In particular, we address two issues. First, we focus on identifying the connection between corruption and risk, determining to which specific risk source corruption belongs and how the market reacts to the announcement. We decompose total risk into systematic and idiosyncratic risk. Risk regressions show that, in its primordial state, the anti-corruption campaign affects both systematic and idiosyncratic risk. Corruption is so widespread that is priced both systematically and individually. Moreover, the effects of the investigation are controversial. The systematic risk of the treatment group does not decrease, suggesting no positive externalities from the announcement, while systematic risk increases for other provinces. Overall, we find that local political instability induced by the campaign increases the market risk through the political risk channel.[2]

[1] According to the Corruption Perceptions Index (CPI), annually released by Transparency International (TI), in 2012, China ranked 80th in cleanliness out of 176 countries or scored 39 on 0 to 100 scale.

[2] Political risk can be triggered by any number of adverse economic, socio-economic, institutional, ethnic, religious or political trend. Economic instability include economic growth, debt ratios and inflation

Given that, our second concern is on determining if market risk's reaction is due to risk shifting among the Chinese provinces.[3] By using intra-daily data, we construct a synthetic index, a value-weighted portfolio, for the affected firms to see if there is any contagion from the treatment group to the rest of the economy immediately after the investigation. We select an event window of 30 trading days centred around the announcement date to see if risk shifting occurs immediately after the announcement. A multiplicative-error term model shows how volatility spillovers exist from the first batch to the others, during our event window, providing evidence of an immediate effect of the anti-corruption campaign over other unaffected areas of the country. A possible future investigation coupled with the potential cost of such investigation including political uncertainty, discontinuity of policies, and inefficiencies arising from lost talents might increase systematic risk for the rest of the economy. At the same time, we find no evidence of the market anticipating the event: from the market's perspective, the investigation come all of sudden. Dynamic volatility forecasts and impulse response functions supports the view that risk shifts, and volatility shocks in the first batch increase the volatility of the unaffected firms.

Unlike many other countries with high corruption, China has high state capacity, which makes the anti-corruption more credible. Therefore, we extend our previous analysis to the second and third batch of the campaign to see how the market reacts as the investigation goes on.

In the second stage, systematic risk decreases for both treatment and control group. Risk regressions do not show any significant difference between the treatment group and the control group in terms of systematic risk. Besides, the multiplicative-error model reveals no risk-shifting among provinces after the announcement. Empirical results for the third batch are in line with the second stage of the campaign. Systematic risk

figures as well as other structural factors, such as competitiveness, unemployment and an extremely unequal distribution of income or wealth. The second risk dimension relates to ethnic, religious, regional and other types of diversity in a country. The last risk dimension comprises institutional factors that could cause social and/or political instability. These factors largely relate to fundamental rights, a high level of corruption and the poor exercise of governance.

[3] Borisov, Goldman, and Gupta (2015) suggest that market inference might not be limited only to the firms in the announced provinces, but it would spill over to all firms in China as market infers that central government will eventually include all provinces in the list for investigation.

decreases for both treatment and control group, with no significant differences between the two groups.

In this paper, we add to the literature by examining the financial effects of the anti-corruption campaign in China and analyse whether such a large-scale campaign really achieved its goal of reducing corruption and political risk, or it was politically motivated and had no real effect on the economy.

Our research contributes to the literature in two-folds. First, we make use of the unique feature Chinese anti-corruption campaign, an extensive monitoring and punishment scheme, to offer insights on the effectiveness of top-down anti-corruption measures.Pei (2007) analyses the key factor for the root causes for China's high level of corruption–partial economic reforms, lax enforcement efforts, and hesitation to adopt political reforms–and the subsequent economic losses and compromised financial stability. Svensson (2005) documents very few successful attempts to fight corruption because the legal and financial institutions employed to fight corruption are weak and corrupt themselves. On the other hand China has the ability to make and effectively implement decisions in domestic and foreign policy, which makes the anti-corruption more credible. We show that, despite an initial negative reaction of the investors, the anti-corruption campaign really achieves its goal from an economic perspective in the second and third batch of the campaign. Systematic risk decreases for both treatment and control group. We offer insights on the policies by showing how a top-down anti-corruption campaign combined with a high-state capacity can beneficial for corporations and investors by reducing the systematic risk. Moreover, fighting corruption holds major implications beyond its borders for foreign investment and international law.

Our paper is also related to the literature on the benefits of the anti-corruption campaign in China. Qian and Wen (2015) and Ke, Liu, and Tang (2016) document a negative impact of the anti-corruption campaign on the consumption of luxury goods. Agarwal et al. (2020) provide evidence that government officials access to credit dropped after the anti-corruption campaign. Zhang (2018) finds that firms are less prone to commit

fraud after the anti-corruption campaign. Lin et al. (2016) look at the value of listed firms and show that more productive firms, firms with more growth potentials and more dependent on external finance benefit more from the campaign. Griffin, Liu, and Shu (2018), instead, documents little evidence that the anti-corruption campaign reduced corporate corruption. Kim, Li, and Tarzia (2018) analyse the market reaction at the time of the investigation and find that the anti-corruption investigation significantly positively influences financial markets in China. We aim to address this gap in the literature with respect to corruption's influence on market risk.

The structure of the paper is as follows. Section 2 looks at the risk profile during the anti-corruption campaign, decomposing total risk into systematic and idiosyncratic risk. Risk regressions are executed using a difference-in-difference analysis. We construct a synthetic measure for each batch in Section 3. Volatility spillovers are studied in Section 4 through the multiplicative-error term model. Dynamic volatility forecasts and impulse response functions conclude the analysis. We repeat the analysis, i.e., risk regressions and volatility spillovers, for further stages of campaign in Section 5. Final remarks follow in Section 6.

2 Systematic and idiosyncratic risks

We decompose a firm's total risk into systematic and idiosyncratic risk by regressing daily returns for firm i at time t on the Fama-French three factors[4]

$$r_{i,t} = \beta_{0,i} + \beta_{1,i} MTK_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \epsilon_{i,t}. \tag{1}$$

The systematic risk is measured as the square root of the explained variance, while the idiosyncratic risk is given by the square root of the unexplained variance (SSR). We estimate the treatment effects using standard difference-in-difference (DID) approach as

[4]See Armstrong and Vashishtha (2012).

below. The risk regressions are

$$Systematic\ risk_{i,t} = \alpha + \gamma Treatment_i + \eta After_t + \delta Treatment_i \times After_t + x_{i,t} + \varepsilon_{i,t}, \quad (2)$$

and

$$Idiosyncratic\ risk_{i,t} = \alpha + \gamma Treatment_i + \eta After_i + \delta Treatment_i \times After_t + x_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where $Treatment$ is one for firms that are located in the province that is announced to be investigated and zero otherwise and $After$ is one for period after the announcement of anti-corruption investigation and zero otherwise. The set $x_{i,t}$ includes all the control variables. We control for firm size (the natural log of total assets, SIZE), liquidity (current assets to current liabilities, LIQ), leverage ratio (total debt to total assets, LEV), operating efficiency (total revenue to total assets, OPEFF), profitability (ROA), revenue growth rate (annual percentage change in revenue, GROWTH), and Tobin's Q (TOBINQ). We also define a dummy variable to indicate state-owned enterprises (SOE) and all regressions include provincial fixed effects.

Our initial sample consists of 2,413 listed companies. We select one year, six month before and six month after the announcement, as event window. The risk measures are estimated on a daily basis while some of our control variables are only available in quarterly frequency. We thus divide the window into four quarters, two quarters before and two quarters after the announcement, and convert the daily risk measures into quarterly values. We winsorize the data at first and 99th percentile, and drop the stocks that have been suspended for more than 30 days. Our final sample consists of 2,381 listed companies.

The treatment group includes all public firms headquartered in Jiangxi, Guizhou, Chongqing, Hubei, and Neimenggu, i.e., the five provinces listed in the first batch of the anti-corruption campaign. The treatment sample includes 184 firms and the control group is composed of 2,197 companies.

[Table 2 about here.]

Panel A in Table 2 reports the descriptive statistics for both treatment and control group for the whole sample. We also subsample for pre- and post-investigation. Systematic risk for the treatment group marginally changes, while idiosyncratic risk increases. The control group, instead, suffers a sharp increase in both systematic and idiosyncratic risk. Overall, both systematic and idiosyncratic risk increase.

[Table 3 about here.]

Table 3 provides the empirical results of Difference-in-Difference model. Columns (1) and (2) report the coefficient of idiosyncratic and systematic risk without control variables.[5] The coefficient of *TreatmentAfter* in column (1) is significant, showing how corruption is priced systematically. Moreover, the negative sign of *TreatmentAfter* in both column (1) and (2) supports the findings that, after the announcement, both systematic and idiosyncratic risks for the treatment group are decreased more than the control group. The coefficient of *After* is positive and significant in both column (1) and (2), showing that the control group, i.e., the other listed companies suffer a significant increase in both systematic and idiosyncratic risk. The treatment group experiences a negligible decrease in the systematic risk when combining the coefficient of *After* and *TreamentAfter*, while the idiosyncratic risk increases. However, the increase in control group's systematic and idiosyncratic risk is substantially higher. Column (3) and (4) reports the DID estimates with control variables. The results on *After* and *TreatmentAfter* are in general in line with those in column (1) and (2). Even with control variables, the systematic risk for the treatment group does not change after the announcement. Overall, systematic risk increase for the Chinese economy.

[Table 4 about here.]

As additional test, we subsample for different control groups. Table 4 provides the empirical results of Difference-in-Difference model when the control group comprises sec-

[5]Please, note that the number of observations is not exactly four times the number of sample firms. We assign a missing value to companies whose trading is suspended for more than 30 days. When a company has two missing value, it is excluded from the sample.

ond, third and fourth batch, respectively. Columns (1) and (2) have the second batch as the control group. Columns (3) and (4) have the third batch, while Columns (5) and (6) have the fourth. Empirical results are in line with what Table 3 suggests. Corruption belongs to the sources of market risk. The systematic risk for the treatment group does not change after the investigation, while increases for the other listed companies.

We conclude that at the end, after the investigation, market risk for the Chinese economy is higher due to the control group.

3 Synthetic index and volatility proxy

Risk regressions in Section 2 show that even the systematic risk of the control group changes. The coefficient of *After* is, indeed, positive in Table 3.

We explore the dynamics of systematic risk for each independent batch to see if changes in the systematic risk of the control group are immediate and attributed to the investigation itself, or due to external factors. As synthetic measures of systematic risk, we construct four portfolios corresponding to the first four batches of anti-corruption investigation. Each portfolio is constructed by the firms listed in the provinces under investigation. For instance, *Portfolio 1* represent the first batch of the anti-corruption campaign.

We construct a value-weighted synthetic index of each portfolio, using the total number of shares. We select a time window of two years around its announcement date, one year before the announcement date and one year after.[6]

The synthetic index is calculated as follows

$$Index_{i,t} = \frac{\sum_{j=1}^{n_i} Price_{j,t} Shares_{j,t}}{\sum_{j=1}^{n_i} Price_{j,0} Shares_{j,0}} Index_0, \tag{4}$$

where n_i is the number of firms in the portfolio i, and $Index_0$ is equal to 1,000 at the

[6]We construct the portfolios based on the total number of shares. Unreported robustness tests only with free-floating shares do not change the empirical findings we provide in the next section.

each starting day.

We use 1-minute interval intra-daily data for all 2,413 stocks from Hexun Database, and measure the realized volatility for each synthetic index with the following volatility proxy[7]

$$hl_t = 100\sqrt{\frac{\pi}{8}}(\log(high_t) - \log(low_t), \tag{5}$$

where $high_t$ and low_t are the highest and lowest daily portfolio prices.

[Table 5 about here.]

Panel A in Table 5 reports the descriptive statistics of the four portfolios for the whole sample. We also subsample for pre- and post-investigation. The volatility proxy for *Portfolio 1* and *Portfolio 2* decline in the post-investigation sample, while it increases for *Portfolio 3* and *Portfolio 4*.

[Figure 2 about here.]

[Figure 3 about here.]

Figure 2 plots the synthetic portfolio indices at the time of the first investigation, while Figure 3 describes the time-series behaviour of the four portfolios from May 2012 to May 2014. The shaded areas correspond to the first announcement period, a window of 30 trading days centred around 29 May 2013, the first announcement day. As shown by the two figures, at the beginning of the event window, *Portfolio 1* has an upward trend. The other three portfolios increase too.

Synthetic indices start to decline immediately after the first announcement period, with a huge spike in volatility in post-announcement period. Even if the magnitude is different among the portfolios, they all show a consistent behaviour, implying that they all suffer a sharp increase in volatility.

[7]The volatility proxy hl can be interpreted as the maximum intradaily return obtainable on a long position entered at the lowest price and closed at the highest (if the former precedes the latter) or on a short position if the highest price was recorded earlier than the lowest. See Parkinson (1980) and Engle, Gallo, and Velucchi (2012) for a detailed discussion on the properties of hl_t.

4 Volatility spillovers

Both Table 5 and Figure 3 point out increase in volatility after the first investigation. However, the entire post-investigation window, is too long to clearly detect immediate effects of the campaign on hl. Given that, in order to deepen our analysis, we focus on volatility spillovers to see how information flows among the Chinese provinces. No volatility spillover indicates that any exogenous shock has no impact on that asset or market itself; vice versa, if spillovers exist, exogenous shocks, due to the transmission of information through a network of interdependencies, can influence related assets or markets depending on the degree of correlation.[8,9]

We model a non-negative process like volatility by a multiplicative error model (MEM). Conditional on the information set I_{t-1}, the volatility for each synthetic index i is

$$hl_{i,t}|I_{t-1} = \mu_{i,t}\varepsilon_{i,t}, \quad i = 1, ..., 4, \tag{6}$$

where the error term $\varepsilon_{i,t}$ is a gamma random variable with unit conditional expectation, that is, with a single parameter ϕ ensuring a large degree of flexibility.

By taking the expectation of Equation (6), we define a base model, a MEM (1,1) involving past values of both hl and its conditional expectation. The base model is

$$\mu_{i,t} = \omega_i + \beta_i\mu_{i,t-1} + \alpha_{i,i}hl_{i,t-1}, \tag{7}$$

where $i = 2, 3, 4$ indicates the second, third and fourth batch, respectively.[10]

By using Equation (7) as the starting point, we enrich the base specification in order to include:

[8] Volatility spillovers refer to how the variation in volatility of asset prices influence volatilities of other markets, in terms of both countries and asset classes.

[9] Ross (1989) claims that volatility of asset prices can reflect the rate of information flow in an arbitrage-free economy.

[10] We only look at volatility spillover effect from *Portfolio 1* to the other portfolios. Therefore, we specify the base model only for the portfolios not being investigated. Moreover, we focus only on uni-directional spillovers and do not evaluate reverse spillover effect from unaffected to affected portfolios.

- Interaction among the affected portfolio, *Portfolio 1* and the unaffected ones i, through the lagged daily ranges observed in the first portfolio $hl_{1,t-1}$;
- Time dummies BC and PC identifying the fifteen trading days before and after the first anti-corruption investigation;
- Interaction terms between daily ranges of all markets and time dummies to accommodate the possibility of changing links during the announcement effect.

The enriched model becomes

$$\mu_{i,t} = \omega + \beta\mu_{i,t-1} + \alpha hl_{i,t-1} + \gamma hl_{1,t-1} + \delta BC_{t-1} + \eta PC_{t-1} + \rho BC_{t-1} hl_{1,t-1} + \tau PC_{t-1} hl_{1,t-1}, \tag{8}$$

where $i = 2, 3, 4$ indicates the second, third and fourth batch, respectively.

We conduct a model selection process to simplify the most general form without losing any explanatory power. We start with the base model in which the conditional expectation of realized volatility is modelled on its past realizations and conditional expected volatility of the market itself; and build our selected model upon the base models. Finally, we expand the model to the most general form, including spillover terms, spillover terms during crisis, and interaction variables as suggested by Equation (8).

For both base and selected model, we report the values of the log-likelihood functions, and the Ljung-Box test statistics for the null of no autocorrelation in the residuals and squared residuals. The estimated gamma parameter ϕ_i for the distribution of standardized residuals is

$$\hat{\phi}^{-1} = \frac{1}{T} \sum_{t=1}^{T} \left(\frac{hl_{i,t}}{\hat{\mu}_{i,t}} - 1 \right)^2. \tag{9}$$

We also define an aggregate portfolio *Aggregate*, including *Portfolio 2*, *Portfolio 3*, and *Portfolio 4*, to see how volatility of *Portfolio 1* spills over to the entire Chinese economy.

[Table 6 about here.]

Table 6 focuses on the volatility spillovers from *Portfolio 1* to *Aggregate*. The interaction term $PC_{t-1}hl_{1,t-1}$ is significant supporting the existence of a spillover effect from the first batch to the unaffected firms immediately after the announcement as shown in column Post(1). We also restrict our time window to one year in order to be consistent with the risk regression. Empirical results in column Post(2) show how the interaction term $PC_{t-1}hl_{1,t-1}$ is even more significant when reducing the time horizon. Local political uncertainty induces volatility spillovers and risk shifts, immediately, to the rest of the Chinese economy. On the other hand, the interaction term $BC_{t-1}hl_{1,t-1}$ provides no evidence of the spillovers before the first announcement, suggesting no information flow before the event. We find no information leakage before the announcement and no evidence of trends prior to the event as shown in Figure 2.[11]

We then divide the control group into three groups based on the anti-corruption batches to see if information flows with different intensity among Chinese provinces.

[Table 7 about here.]

The column Post(2) in Table 7 focuses on the spillover effect from *Portfolio 1* to *Portfolio 2*. The interaction term $PC_{t-1}hl_{1,t-1}$ is not significant, providing no evidence of an immediate spillover effect from the first batch to the second batch. *Portfolio 2* does not react to volatility shocks after the announcement. The second batch does not react to the local political uncertainty induced by the campaign.

The column Post(3) shows, instead, evidence of a spillover effect from *Porftolio 1* to *Portfolio 3*. The interaction between the volatility proxy and the post-event variable is significant, showing a significant effect from the first batch to the third batch. Information immediately flows from the first batch to the third batch. The market reacts to the announcement, pushing up, immediately, the systematic risk for the third batch.

The column Post(4) supports the existence of a spillover effect from *Porftolio 1* to *Portfolio 4*. The interaction term $PC_{t-1}hl_{1,t-1}$ is slightly significant but bigger in magnitude with to respect to *Portfolio 4*, suggesting an immediate reaction by investors.

[11] Unreported results with twenty trading days as event window are qualitatively similar.

We also implement dynamic forecasts to study the volatility patterns of each portfolio during the announcement period, over 90 trading days. We start from 15 trading days before the announcement date, and move repeatedly the starting point by one day until 15 days after the announcement day so that the newly arrived information is reflected in the forecasts. This moves ahead and changes the forecast profile due to newly observed starting values reflecting the market conditions that the forecasts are conditioned on. All profiles converge to the same long-run average volatility implied by the model estimates.

We define a dummy variable DC, identifying 30 trading days around the announcement date, i.e., 15 trading days before and after the announcement date. Based on the information available at time t, the conditional expectation of hl_{t+1} for each portfolio can be written compactly as[12]

$$\boldsymbol{\mu}_{t+1} \quad = \boldsymbol{\omega}^* + \boldsymbol{\eta} DC_t + \boldsymbol{B}\boldsymbol{\mu}_t + \boldsymbol{A}^* \boldsymbol{hl}_t + \boldsymbol{\Gamma} \boldsymbol{hl_t} DC_t. \tag{10}$$

Moving steps forward makes $\boldsymbol{hl}_{t+\tau}$, $\tau > 0$, unknown and needs to be proxied with its conditional expectation $\boldsymbol{\mu}_{t+\tau}$. The dummy DC is fixed to the value that both variables have in t. Hence, for $\tau = 2$

$$\begin{aligned} \boldsymbol{\mu}_{t+2} \quad &= \boldsymbol{\omega}^* + \boldsymbol{\eta} DC_t + \boldsymbol{B}\boldsymbol{\mu}_{t+1} + \boldsymbol{A}^* \boldsymbol{\mu}_{t+1} + \boldsymbol{\Gamma} \boldsymbol{\mu_{t+1}} DC_t \\ &= \boldsymbol{\omega}^* + \boldsymbol{\eta} DC_t + (\boldsymbol{B} + \boldsymbol{A}^* + \boldsymbol{\Gamma} DC_t) \boldsymbol{\mu}_{t+1}, \end{aligned} \tag{11}$$

and, recursively, for $\tau > 2$[13]

[12] Engle and Gallo (2006) show better performance in predicting VIX than $AR(1)$ model.

[13] It should be noted that, in order to forecast the dynamics of the volatility proxy, we need to initialize Equation (10) by estimating the coefficients, because we have a different dummy variable, DC.

$$
\begin{aligned}
\boldsymbol{\mu}_{t+\tau} &= \boldsymbol{\omega}^* + \boldsymbol{\eta} DC_t + (\boldsymbol{B} + \boldsymbol{A}^* + \boldsymbol{\Gamma} DC_t)\boldsymbol{\mu}_{t+\tau-1} \\
&= \boldsymbol{\omega} + \boldsymbol{A}_1 \boldsymbol{\mu}_{t+\tau-1}. \qquad (12)
\end{aligned}
$$

[Figure 6 about here.]

Figure 6 shows the dynamics of the portfolios. In figure 6 the left plot shows the dynamics of *Portfolio 1*, while the right graph displays the dynamics of *Aggregate*, that includes *Portfolio 2*, *Portfolio 3* and *Portfolio 4*. The three vertical lines indicate 15 trading days before announcement date, the announcement date, and 15 trading days after announcement date, respectively.

Volatility increases for all portfolios after the announcement date, indicating that, both at the aggregate and the local level, all firms are more or less influenced by the anti-corruption campaign. The evolution of the dynamic forecast supports the existence of volatility spillovers. *Portfolio 1* can be seen as reacting mainly to its own innovations. Studying the profiles along vertical lines (for example, 24 June), we document an increase in the progressive volatility forecasts until the beginning of July, after which it subsides. In *Aggregate* the volatility forecasts exhibit an increasing trend until the beginning of September, after which all profiles converge to the same long-run average volatility implied by the model estimates, much higher than *Portfolio 1*.

In other words, even if only five provinces are under investigation during the first batch of the anti-corruption investigation, all other unaffected provinces respond to the news, supporting the previous findings that information flow causes systematic risk of unaffected companies to increase.

As final check, we compute the impulse response functions (IRF) to determine how each portfolio reacts to shocks. Equation (6) can be rearranged so that the MEM can be seen as a unique block rather than a single entry, and the variable *hl* can be considered as whole system.

$$\boldsymbol{hl}_t = \boldsymbol{\mu}_t \odot \boldsymbol{\varepsilon}_t, \tag{13}$$

with $\boldsymbol{hl}_t$ being a vector with stacked $hl_{i,t}$'s, $\boldsymbol{\mu}_t$ representing a vector with stacked $\mu_{i,t}$'s, and $\boldsymbol{\varepsilon}_t$ defining a jointly multivariate independently identically distributed vector with expected value equal to 1 and variance-covariance matrix denoted as $\boldsymbol{\Sigma}$. The symbol $\odot$ represents the element-by-element multiplication.

The conditional expectation of $\boldsymbol{hl_{t+\tau}}$ can be seen as the expected value of $\boldsymbol{hl_{t+\tau}}$ when $\boldsymbol{\varepsilon}_t$ is equal to the unit vector $\mathbf{1}$

$$\boldsymbol{\mu}_{t+\tau} = E(\boldsymbol{hl}_{t+\tau}|I_t, \boldsymbol{\varepsilon}_t = \mathbf{1}) \tag{14}$$

By defining a generic vector of shocks $\mathbf{s}^{(i)}$, we can derive a different dynamic solution[14]

$$\boldsymbol{\mu}^{(i)}_{t+\tau} = E(\mathbf{hl}_{t+\tau|I_t}, \boldsymbol{\varepsilon}_t = \mathbf{1} + \mathbf{s}^{(i)}) \tag{16}$$

Then, we can derive the relative change in expected volatility in vector form[15]

$$\rho^{(i)}_{t,\tau} = (\boldsymbol{\mu}^{(i)}_{t+\tau} \oslash \boldsymbol{\mu}_{t+\tau}) - \mathbf{1}, \quad \tau = 1, ..., K. \tag{17}$$

[14]We derive Equation (16) by posing the ith element equal to the unconditional standard deviation of ε_{it} and the other terms $j \neq i$ equal to the linear projection

$$E(\varepsilon_{j,t}|\varepsilon_{i,t} = 1 + \sigma_i) = 1 + \sigma_i \frac{\sigma_{i,j}}{\sigma_i^2}. \tag{15}$$

[15]Pericoli and Sbracia (2003) and Dungey and Martin (2007) define contagion in terms of correlated shocks as well.

with $\oslash$ representing the element-by-element division. Equation (17) allows us to observe the relative changes in the forecast profile starting at time t for a horizon τ brought about by a 1 standard deviation shock in *Portfolio i*.[16]

We select the announcement date as starting date for the IRF. Similar to the dynamic volatility forecasts, the time-horizon consists of 90 trading days.

[Figure 7 about here.]

Figure 7 plots the impulse response functions for *Portfolio 1* and *Aggregate*, that comprises *Portfolio 2*, *Portfolio 3* and *Portfolio 4*. The largest effect for *Aggregate* is almost coincident with the shocks. We observe a high impact on *Portfolio 1* (about 40%) with a monotonically declining response. The impact is even higher for *Aggregate*, (about 45%), that reaches its peak just few days later (less than 10 days). The shock is not that transitory, since, after reaching the peak, *Aggregate* does not decay quickly. Shocks in *Portfolio 1* affect *Aggregate* for a little over two months.

[Figure 8 about here.]

Based on the different reactions shown in Table 7, we study the impulse response function for each individual portfolio. Among the three portfolios, *Portfolio 3* is the one with the highest impact (about 50%), in line with results provided in Table 9. Shock in *Portfolio 1* affect *Aggregate* for almost three months. Vice versa, *Portfolio 2* exhibits lesser signs of being affected by the shock. In line with results provided in Table 7, *Portfolio 2* reacts less with respect to *Portfolio 3* and its response function decays faster. *Portfolio 4* reacts more than *Portfolio 2*, but it exhibits a faster decays. After 60 days, the impulse response function of *Portfolio 2* and *Portfolio 4* are almost identical.

We conclude that risk shifts immediately after the announcement to the entire system, and, as suggested by Table 7 and Figure 8, is mainly driven by volatility spillovers between *Portfolio 1* and *Portfolio 3* and *Portfolio 1* and *Portfolio 4*, respectively.

[16] Dungey and Martin (2007) provides an impulse response function in a GARCH contest, but the advantage of a MEM stands in its ability to capture momentum.

5 Subsequent batches

We extend the previous analysis, i.e., risk regression and volatility spillovers, to the second batch of the anti-corruption campaign. When executing risk regressions, we omit from our sample all listed firms belonging to the first treatment group. Panel B in Table 2 reports the descriptive statistics for both treatment and control group. We also subsample for pre- and post-investigation. Both systematic and idiosyncratic risk for the treatment group are lower with respect to pre-event values. However, they are not significantly different with respect to the control group.

[Table 8 about here.]

Table 8 reports the difference-in-difference estimates for the second batch. Columns (1) and (2) report the estimates when the treatment group is the second batch, and the control group includes both third and fourth batches. The coefficient estimate of *TreatmentAfter* is not significant in any of the risk regressions, supporting the findings that there is no significant difference in systematic and idiosyncratic risks between the treatment and control group. Both systematic and idiosyncratic risks decrease after the investigation, but there is not significant difference between treatment and control group.

No significant difference between treatment and control group might signal no immediate risk shifts among provinces. As for the first investigation, we construct three portfolios to measure volatility spillovers and risk-shifting among regions. Consistent with the risk regression in Table 8, we exclude from our analysis the firms belonging to the first batch.

Descriptive statistics are reported in Table 5, Panel B. For all three portfolios, volatility decreases after the event. Given that, as in Section 4, we focus on spillovers among portfolios.

[Table 9 about here.]

Column Base Model (1) and Selected Model (1) in Table 9 focus on the spillover effect

from *Portfolio 2*, to an aggregate portfolio, *Aggregate*, including *Portfolio 3*, *Portfolio 4*. The interaction term $PC_{t-1}hl_{2,t-1}$ is not significant, indicating no spillover from the second batch to the unaffected firms, immediately after the investigation. The decrease in systematic risk for the control group shown in Table 8 might not be related to information flows. As before, we also look at volatility patterns and impulse response functions for the second batch.

[Figure 9 about here.]

Figure 9 shows the forecast dynamics during second batch investigation. The left figure shows the dynamics of *Portfolio 2*, while the right graph displays the dynamics of *Aggregate*, that comprises *Portfolio 3*, *Portfolio 4*. Volatility patterns are slightly different from that of the first batch announcement. *Portfolio 2* can be seen as reacting mainly to its own innovations. Studying the profiles along vertical lines (for example, 21 November), we document an increase in the progressive volatility forecasts until the beginning of December, after which it subsides. In *Aggregate* the volatility forecasts exhibit an increasing trend until the beginning of November, after which all profiles converge to the same long-run average volatility implied by the model estimates, sligthly smaller than *Portfolio 2*. The second batch, indeed, exhibits a downward trend and does not provide any evidence of volatility spillovers. Even if the systematic risk for the control group decreases after the announcement, we find no evidence of immediate risk-shifting among provinces.

[Figure 10 about here.]

Figure 10 plots the impulse response functions for *Portfolio 2*, and *Aggregate*, that includes *Portfolio 3* and *Portfolio 4*.

We notice a high impact on *Portfolio 2* (more than 40%) with a monotonically declining response, while the reaction of *Aggregate* is much weaker. The impulse response function of *Aggregate* is much steeper and reaches its lowest value after 20 days. After touching its minimum, it increases slowly over the next 70 days.

Then, we study the third batch. Panel B in Table 2 reports the descriptive statistics for both treatment and control group. We also subsample for pre- and post-investigation. As for the second batch, both systematic and idiosyncratic risk for the treatment group are lower with respect to pre-event values. Similarly, they are not significantly different with respect to the control group. Columns (3) and (4) in Table 8 report the estimates when the treatment group is the third batch, and the control group includes only the fourth batch. Empirical results are in line with Columns (1) and (2), i.e., no significant difference in systematic and idiosyncratic risks between the treatment and control group. Again, both systematic and idiosyncratic risks decrease after the investigation, but there is not a significant difference between treatment and control group. Column Base Model (1) and Selected Model (1) in Table 9 focus on the spillover effect from *Portfolio 3*, to *Portfolio 4*. Different from the second batch, the interaction term $PC_{t-1}hl_{3,t-1}$ is significant with a negative sign. The decrease in systematic risk for the control group shown in Table 8 might be strongly related to information flows, generating a trend reversal in the volatility pattern.[17]

[Figure 11 about here.]

Figure 11 plots the volatility forecasts for the third stage of the investigation. The left figure shows the dynamics of *Portfolio 3*, while on the right the dynamics of *Portfolio 4* is plotted. *Portfolio 3* can be seen as reacting mainly to its own innovations. Studying the profiles along vertical lines (for example, 15 May), we document an increase in the progressive volatility forecasts until the beginning of June, after which it subsides. In *Portfolio 4* the volatility forecasts exhibit a decreasing trend until the mid of April, after which all profiles converge to the same long-run average volatility implied by the model estimates, similar to *Portfolio 3*.

[Figure 12 about here.]

Figure 12 plots the impulse response functions for *Portfolio 3* and *Portfolio 4*. As above, we observe a high impact (more than 40%) for the originating portfolio, *Portfolio*

[17]Based on Engle and Gallo (2006), a negative coefficient might be interpreted as a "sign of the daily range (or hilo) being indicators of a trend reversal in periods of high volatility".

3, with a monotonically declining response. *Portfolio 4* exhibits, again, a sharp decrease. Its IRF reaches its minimum after twelve days: the effect is much more pronounced with respect to second batch (-170% versus 20%). After reaching the minimum, the impulse response function increases over the next seventy-eight days, much faster than the second batch.

Both second and third round of the anticorruption campaign are characterized by a decrease in systematic risk for the control group. Moreover, shocks in the affected portfolios do not propagate to the other batches, rejecting the hypothesis of volatility spillovers from one group to the others. The second batch exhibits no risk shifting among batches, while the third batch shows a trend reversal in the short run as suggested by the sign of $PC_{t-1}hl_{3,t-1}$.

6 Conclusions

We make use of the anti-corruption campaign to determine if corruption in China is only restricted to to individual firms or has been affecting the Chinese political and economic system for such long time representing an entire risk for the whole system.

Our results support that the different stages of the anti-corruption campaign are characterized by different dynamics for systematic and idiosyncratic risk. By using a difference-in-difference model, we find that the first stage of the investigation reduces both idiosyncratic and systematic risk for the treatment group with respect to the control group. Overall, systematic risk slightly changes for the treatment group, while increases for the rest of economy. The first stage of the investigation is characterized by volatility spillovers from the affected portfolio to the rest of country, indicating that the campaign has a deep impact on the entire Chinese system, as shown by volatility forecasts and impulse response functions. Risk shifts immediately among different regions of the Chinese economy.

Second and third stage investigation exhibits no significant difference between treatment and control group in terms of risk sources, suggesting no spillovers among regions.

Shocks do not propagate from one portfolio to the other ones for the second stage, while some trends in volatility arise in the third round of the campaign. Systematic risk, surprisingly, increases again when individual firms are investigated. In the run-up to the subsequent investigation, we find evidence of spillovers, most likely due to some information leakage.

Our results suggest avenues for future research that could exploit data on individual firm, industries or individual provinces, in order to see how complex inter-industry or inter-regional interdependencies might significantly contribute to volatility spillovers. The volatility spillovers exhibit different intensity depending on the portfolio and the geographical area considered, as shown by our empirical analysis. Determining how strong is the link between interdependencies and volatility spillovers might be relevant for investors and regulators.

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Table 1: Timeline of the anticorruption campaign

This table reports the sequence, the name, the batch, the announcement date and the ending date (month/day/year) of the anticorruption campaign for each Chinese province.

No.	Province	Batch	Announcement date	Ending date
		Year 2013		
1	Jiangxi	first	29 May	20 August
2	Guizhou	first	29 May	29 July
3	Chongqing	first	29 May	29 July
4	Hubei	first	2 June	23 July
5	Neimenggu	first	3 June	6 August
6	Jilin	second	30 October	26 December
7	Guangdong	second	30 October	28 December
8	Yunnan	second	30 October	28 December
9	Shanxi	second	30 October	29 December
10	Anhui	second	31 October	27 December
11	Hunan	second	1 November	30 December
		Year 2014		
12	Hainan	third	24 March	27 May
13	Fujian	third	27 March	26 May
14	Gansu	third	27 March	27 May
15	Henan	third	28 March	27 May
16	Tianjin	third	28 March	28 May
17	Shandong	third	29 March	28 May
18	Xinjiang	third	30 March	24 May
19	Liaoning	third	30 March	25 May
20	Beijing	third	31 March	30 May
21	Ningxia	third	31 March	31 May
22	Xizang	fourth	25 July	24 September
23	Qinghai	fourth	26 July	29 September
24	Guangxi	fourth	28 July	27 September
25	Jiangsu	fourth	28 July	27 September
26	Heilongjiang	fourth	28 July	27 September
27	Sichuan	fourth	28 July	28 September
28	Hebei	fourth	29 July	25 September
29	Zhejiang	fourth	29 July	28 September
30	Shanghai	fourth	29 July	30 September
31	Shaanxi	fourth	30 July	28 September

Table 2: Descriptive statistics for the risk regressions

This table reports the mean, standard deviation (S.D.), minimum (min) and maximum (max) for idiosyncratic (IDIO) and systematic (SYS) risk at the time of the first investigation. The two risk variables are computed for the entire sample, the treatment and the control group.

		Mean	S.D.	Min	Max
IDIO					
	Whole Sample	0.1516	0.0544	.0276	0.4487
	Pre-event	0.1427	0.0495	0.0276	0.3969
	Post-event	0.1605	.0575	.0380	.4487
SYS					
	Whole Sample	0.1233	0.0384	0.0174	0.2839
	Pre-event	0.1207	0.0331	0.0174	0.2488
	Post-event	0.1260	0.0429	0.0186	0.2839
Treatment group					
IDIO					
	Whole Sample	0.1485	0.0531	.0380	.3969
	Pre-event	0.1472	0.0538	0.0380	0.3969
	Post-event	0.1499	0.0523	0.0465	0.3644
SYS					
	Whole Sample	0.1183	0.0370	0.0223	0.2608
	Pre-event	0.1185	0.0311	0.0264	0.2026
	Post-event	0.1182	0.0421	0.0223	0.2608
Control group					
IDIO					
	Whole Sample	0.1518	0.0545	0.0276	0.4487
	Pre-event	0.1423	0.0491	0.0276	0.3430
	Post-event	0.1614	0.0578	0.03808	0.4487
SYS					
	Whole Sample	0.1237	0.0385	0.0174	0.2839
	Pre-event	0.1209	0.0334	0.0174	0.2488
	Post-event	0.1266	0.0429	0.0186	0.2839

Sources: Wind database

Table 3: Risk regressions at the time of the first investigation

This table provides the difference-in-difference estimates for both idiosyncratic and systematic risk during the first batch of the anticorruption campaign.

$$Idiosyncratic\ risk_{t,i} = \alpha + \gamma Treatment_i + \eta After_i + \delta TreatmentAfter_{i,t} + x_{i,t} + \varepsilon_{i,t},$$
$$Systematic\ risk_{t,i} = \alpha + \gamma Treatment_i + \eta After_i + \delta TreatmentAfter_{i,t} + x_{i,t} + \varepsilon_{i,t}.$$

	(1)	(2)	(3)	(4)
	IDIO	SYS	IDIO	SYS
Treatment	0.0081	-0.0045	0.0034	-0.0036
	(0.0077)	(0.0047)	(0.0081)	(0.0051)
After	0.0184***	0.0055***	0.0175***	0.0061***
	(0.0010)	(0.0006)	(0.0010)	(0.0006)
TreatmentAfter	-0.0160***	-0.0058***	-0.0157***	-0.0060***
	(0.0010)	(0.0006)	(0.0010)	(0.0006)
SOE			-0.0042***	-0.0019
			(0.0016)	(0.0012)
SIZE			-0.049***	-0.0022***
			(0.0008)	(0.0006)
LIQ			0.0007***	0.0007***
			(0.0002)	(0.0002)
LEV			0.0226***	-0.0178***
			(0.0052)	(0.0034)
OPEFF			-0.0292*	0.0234**
			(0.0170)	(0.0109)
ROA			-0.0001	-0.0005*
			(0.0004)	(0.0003)
GROWTH			0.0009	-0.0022***
			(0.0013)	(0.0008)
TOBINQ			0.0111***	-0.0016***
			(0.0008)	(0.0005)
Intercept	0.1356***	0.1155***	0.2209***	0.1734***
	(0.0042)	(0.0024)	(0.0161)	(0.0133)
Province fixed effects	YES	YES	YES	YES
Observations	9,351	9,351	9,325	9,325
Stocks	2,381	2,381	2,381	2,381
Within R^2	0.0548	0.0095	0.0900	0.0113

Notes: Robust standard errors are shown in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4: Risk regressions at the time of the first investigation

This table provides the difference-in-difference estimates for both idiosyncratic and systematic risk during the first batch of the anticorruption campaign.

$$Idiosyncratic\ risk_{i,t} = \alpha + \gamma Treatment_i + \eta After_i + \delta TreatmentAfter_{i,t} + x_{i,t} + \varepsilon_{i,t},$$
$$Systematic\ risk_{i,t} = \alpha + \gamma Treatment_i + \eta After_i + \delta TreatmentAfter_{i,t} + x_{i,t} + \varepsilon_{i,t}.$$

	(1)	(2)	(3)	(4)	(5)	(6)
	IDIO	SYS	IDIO	SYS	IDIO	SYN
Treatment	0.0012	-0.0034	-0.0067	-0.0136***	0.0080	0.0022
	(0.0080)	(0.0048)	(0.0077)	(0.0050)	(0.0096)	(0.0064)
After	0.0128***	0.0049***	0.0172***	0.0072***	0.0208***	0.0059***
	(0.0020)	(0.0012)	(0.0017)	(0.0011)	(0.0016)	(0.0010)
TreatmentAfter	-0.0110***	-0.0046**	-0.0151***	-0.0071***	-0.0194***	-0.0059***
	(0.0040)	(0.0022)	(0.0039)	(0.0021)	(0.0038)	(0.0021)
SOE	-0.0078***	0.0004	-0.0032	-0.0021	-0.0016	-0.0003
	(0.0028)	(0.0021)	(0.0024)	(0.0019)	(0.0025)	(0.0017)
SIZE	-0.0023	0.0001	-0.0085***	-0.0030***	-0.0022*	-0.0014
	(0.0015)	(0.0011)	(0.0011)	(0.0010)	(0.0012)	(0.0009)
LIQ	0.0007**	0.0005**	0.0005	0.0007***	0.0007*	0.0006***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
LEV	0.0193**	-0.0295***	0.0239***	-0.0239***	0.0229***	-0.0165***
	(0.0082)	(0.0055)	(0.0085)	(0.0052)	(0.0076)	(0.0049)
OPEFF	-0.0012	0.0217	-0.0170	0.0180	-0.0677***	0.0181
	(0.0290)	(0.0185)	(0.0268)	(0.0179)	(0.0258)	(0.0159)
ROA	0.0000	0.0001	-0.0002	-0.0004	0.0005	0.0001
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0008)	(0.0006)
GROWTH	0.0011	-0.0012	0.0020	-0.0020	0.0005	-0.0018
	(0.0022)	(0.0012)	(0.0019)	(0.0013)	(0.0019)	(0.0012)
TOBINQ	0.0096***	-0.0024***	0.0091***	-0.0022***	0.0129***	-0.0011
	(0.0012)	(0.0007)	(0.0012)	(0.0007)	(0.0012)	(0.0008)
Intercept	0.1681***	0.1297***	0.3098***	0.2068***	0.1520***	0.1495***
	(0.0308)	(0.0232)	(0.0226)	(0.0213)	(0.0266)	(0.0197)
Province fixed effects	YES	YES	YES	YES	YES	YES
Observations	3,043	3,043	3,467	3,467	4,249	4,249
Stocks	780	780	887	887	1082	1082
Within R^2	0.0571	0.0120	0.0748	0.0133	0.1020	0.0078

Notes: Robust standard errors are shown in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Columns (1) and (2) have the second batch as the control group.

Columns (3) and (4) have the third batch, while Columns (5) and (6) have the fourth.

Table 5: Descriptive statistics for the volatility proxy *hl*

This table reports the mean, median, the minimum, maximum, standard deviation (S.D.), skewness and kurtosis for the volatility proxy *hl*. Whole Sample represents the overall mean, while Pre-event and Post-event are the mean before and after the event. Panel A, Panel B and Panel C report the statistics for the first, second and third investigation, respectively.

Panel A: First investigation				
	Portfolio 1	*Portfolio 2*	*Portfolio 3*	*Portfolio 4*
Whole Sample	0.4518	0.4638	0.3252	0.4414
Pre-event	0.4597	0.4650	0.3130	0.4241
Post-event	0.4439	0.4626	0.3374	0.4587
Median	0.4067	0.4128	0.2785	0.3913
Minimum	0.1354	0.1351	0.0966	0.1383
Maximum	2.1892	2.2370	1.4087	1.9926
S.D	0.2188	0.2281	0.1710	0.2116
Skewness	2.3103	2.3718	2.1810	2.2711
Kurtosis	14.0597	13.8404	10.3866	12.6122
Panel B: Second investigation				
		Portfolio 2	*Portfolio 3*	*Portfolio 4*
Whole Sample	-	0.4392	0.3213	0.4262
Pre-event	-	0.5050	0.3573	0.4700
Post-event	-	0.3734	0.2853	0.3824
Median	-	0.3829	0.2802	0.3819
Minimum	-	0.1217	0.1006	0.1310
Maximum	-	2.2370	1.4087	1.9926
S.D	-	0.2281	0.1710	0.2116
Skewness	-	2.4707	2.1832	2.3602
Kurtosis	-	14.4044	10.7685	13.1001
Panel C: Third investigation				
			Portfolio 3	*Portfolio 4*
Whole Sample	-	-	0.3814	0.4390
Pre-event	-	-	0.3410	0.4634
Post-event	-	-	0.4218	0.4146
Median	-	-	0.3098	0.3889
Minimum	-	-	0.1006	0.1310
Maximum	-	-	2.3221	1.9926
S.D	-	-	0.2667	0.2291
Skewness	-	-	2.6469	2.5557
Kurtosis	-	-	12.8146	14.2283

Sources: Hexun database

Table 6: Volatility spillovers at the time of the first investigation

This table reports the MEM-estimates from the first portfolio, *Portfolio 1*, to the aggregate portfolio, *Aggregate*, at the time of the first investigation.

$$\mu_{aggr.,t} = \omega + \beta\mu_{aggr.,t-1} + \alpha hl_{aggr,,t-1} + \gamma hl_{1,t-1} + \delta BC_{t-1} + \eta PC_{t-1} + \rho BC_{t-1}hl_{1,t-1} + \tau PC_{t-1}hl_{1,t-1}.$$

The coefficient estimates are shown for the base (Base model) and the selected model (Selected model) before and after the investigation effect. Column Pre, Post(1) and Post(2) focuses on the interaction between *Portfolio 1* and *Portfolio Aggregate* before and after the announcement, respectively. LogLik is the value of the log likelihood. SIC and AIC are the Schwarz Criterion and Akaike information criterion, respectively. CORR(12) (respectively, CORRSQ(12)) is the LM test statistic for autocorrelation up to order 12 in the standardized residuals $\frac{h_t}{\hat{\mu}_t}$ (respectively, squared standardized residuals $\frac{h_t^2}{\hat{\mu}_t^2}$) with the corresponding p-values in parentheses. ϕ is the estimated method of moments gamma parameter.

	Base Model	Selected Model		
		Pre	Post(1)	Post(2)
ω	0.0275	0.0285	0.0219***	0.0415***
	(0.0186)	(0.0190)	(0.0080)	(0.0158)
$\mu_{aggregate,t-1}$	0.8396***	0.8311***	0.9068***	0.8733***
	(0.0864)	(0.0904)	(0.0324)	(0.0591)
$hl_{aggregate,t-1}$	0.0863*	0.0641	0.0243	-0.0411
	(0.0443)	(0.0459)	(0.0238)	(0.0513)
$hl_{1,t-1}$		0.0234	0.0056	0.0512
		(0.0259)	(0.0160)	(0.0379)
BC_{t-1}		0.0428		
		(0.0794)		
PC_{t-1}			-0.0580	-0.0895*
			(0.0416)	(0.0478)
$BC_{t-1}hl_{1,t-1}$		-0.1270		
		(0.2014)		
$PC_{t-1}hl_{1,t-1}$			0.2027*	0.2744**
			(0.1100)	(0.1251)
Loglik	-440.7408	-440.6518	-439.5526	-229.6269
SIC	1.8789	1.9172	1.9126	2.0590
AIC	1.8528	1.8649	1.8603	1.9718
LB(12)	3.5431	3.6843	4.5894	5.1889
	(0.990)	(0.988)	(0.970)	(0.951)
LBSQ(12)	11.7190	10.6300	6.6030	4.8160
	(0.469)	(0.561)	(0.883)	(0.964)
$\hat{\phi}$	4.4763	4.5400	4.9216	4.7371

Notes: Robust standard errors are shown in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7: Volatility spillovers at the time of the first investigation

This table reports the MEM-estimates from the first portfolio, *Portfolio 1*, to the second portfolio, *Portfolio 2*, third portfolio, *Portfolio 3* and fourth portfolio, *Portfolio 4* at the time of the first investigation.

$$\mu_{i,t} = \omega + \beta\mu_{i,t-1} + \alpha hl_{i,t-1} + \gamma hl_{1,t-1} + \delta BC_{t-1} + \eta PC_{t-1} + \rho BC_{t-1}hl_{1,t-1} + \tau PC_{t-1}hl_{1,t-1}, \text{ i=2,3,4.}$$

The coefficient estimates are shown for the selected model after the investigation effect. Column Post(1), Post(2) and Post(3) focuses on the interaction between *Portfolio 1* and *Portfolio 2*, *Portfolio 3*, *Portfolio 4*, respectively. LogLik is the value of the log likelihood. SIC and AIC are the Schwarz Criterion and Akaike information criterion, respectively. CORR(12) (respectively, CORRSQ(12)) is the LM test statistic for autocorrelation up to order 12 in the standardized residuals $\frac{h_t}{\hat{\mu}_t}$ (respectively, squared standardized residuals $\frac{h_t^2}{\hat{\mu}_t^2}$) with the corresponding p-values in parentheses. ϕ is the estimated method of moments gamma parameter.

	Selected Model		
	Post (1)	Post (2)	Post (3)
ω	0.0257**	0.0168**	0.0331***
	(0.0092)	(0.0070)	(0.0116)
$\mu_{2,t-1}$	0.9042***		
	(0.0317)		
$hl_{2,t-1}$	0.0730		
	(.0302)		
$\mu_{3,t-1}$		0.8961***	
		(0.0342)	
$hl_{3,t-1}$		0.0490**	
		(0.0232)	
$\mu_{4,t-1}$			0.9047***
			(0.0362)
$hl_{4,t-1}$			0.0101
			(0.0265)
$hl_{1,t-1}$	0.0137	0.0005	0.0069
	(0.0168)	(0.0137)	(0.0205)
PC_{t-1}	-0.0542	-0.0560*	-0.0709
	(0.0535)	(0.0338)	(0.0541)
$PC_{t-1}hl_{1,t-1}$	0.2242	0.1848**	0.2483*
	(0.1431)	(0.0907)	(0.1406)
Loglik	-492.5859	-407.5717	-481.6458
SIC	2.1340	1.7791	2.0884
AIC	2.0818	1.7268	2.0361
LB(12)	6.5481	6.3295	8.0561
	(0.886)	(0.899)	(0.781)
LBSQ(12)	5.3628	11.8650	8.4083
	(0.945)	(0.457)	(0.752)
$\hat{\phi}$	5.3550	4.3259	5.3025

Notes: Robust standard errors are shown in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8: Risk regressions at the time of the second and third investigation

This table provides the difference-in-difference estimates for both idiosyncratic and systematic risk for the second and third batch of the anticorruption campaign.

$$\begin{aligned} \textit{Idiosyncratic risk}_{i,t} &= \alpha + \gamma Treatment_i + \eta After_i + \delta TreatmentAfter_{i,t} + x_{i,t} + \varepsilon_{i,t} \\ \textit{Systematic risk}_{i,t} &= \alpha + \gamma Treatment_i + \eta After_i + \delta TreatmentAfter_{i,t} + x_{i,t} + \varepsilon_{i,t} \end{aligned} ,$$

	(1)	(2)	(3)	(4)
	IDIO	SYS	IDIO	SYS
Treatment	-0.0091*	0.0008	0.0017	0.0116***
	(0.0080)	(0.0033)	(0.0037)	(0.0025)
After	-0.0107***	-0.0086***	-0.0264***	-0.0362***
	(0.0011)	(0.0007)	(0.0017)	(0.0010)
TreatmentAfter	0.0016	-0.0020	0.041	0.0016
	(0.0022)	(0.0014)	(0.0025)	(0.0014)
SOE	-0.0072***	-0.0051***	-0.0066***	-0.0054***
	(0.0018)	(0.0013)	(0.0020)	(0.0014)
SIZE	-0.0045***	0.0010***	0.0011***	-0.0080***
	(0.0009)	(0.0006)	(0.0009)	(0.0006)
LIQ	0.0008**	0.0010**	0.0011***	0.0008***
	(0.0003)	(0.0002)	(0.0004)	(0.0003)
LEV	0.0190**	-0.0192***	0.0331***	-0.0124***
	(0.0061)	(0.0039)	(0.0066)	(0.0040)
OPEFF	-0.0383***	0.0101	-0.0610***	-0.0027
	(0.0180)	(0.0108)	(0.0200)	(0.0131)
ROA	-0.0007	-0.0005*	0.0002	-0.0006
	(0.0005)	(0.0003)	(0.0006)	(0.0004)
GROWTH	0.0051***	-0.0022*	0.0062***	-0.0008
	(0.0019)	(0.0012)	(0.0020)	(0.0013)
TOBINQ	0.0137***	0.0001	0.0099***	-0.005
	(0.0009)	(0.0005)	(0.0008)	(0.0005)
Intercept	0.2281***	0.2147***	0.2934***	0.2511***
	(0.0181)	(0.0131)	(0.0196)	(0.0124)
Province fixed effects	YES	YES	YES	YES
Observations	8,539	8,539	6,103	6,103
Stocks	2,187	2,187	1,574	1,574
Within R^2	0.0786	0.0329	0.115	0.379

Notes: Robust standard errors are shown in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Columns (1) and (2) have the second batch as treatment group, with third and fourth as control group.

Columns (3) and (4) have the third batch as treatment group, with the fourth batch as control group.

Table 9: Volatility spillovers at the time of the second and third investigation

This reports the MEM-estimates from the second and third portfolio, *Portfolio 2* and *Portfolio 3*, to the aggregate portfolio, *Aggregate*, at the time of the second and third investigation investigation.

$$\mu_{aggr.,t} = \omega + \beta\mu_{aggr.,t-1} + \alpha hl_{aggr.,t-1} + \gamma hl_{i,t-1} + \delta BC_{t-1} + \eta PC_{t-1} + \rho BC_{t-1}hl_{i,t-1} + \tau PC_{t-1}hl_{i,t-1}, \text{ i=2,3.}$$

The coefficient estimates are shown for the base (Base model) and the selected model (Selected model) before and after the investigation effect. Column Pre(1) and Post 1) focuses on the interaction between *Portfolio 2* and textitPortfolio Aggregate before and after the announcement, respectively. Column Pre(2) and Post(2) focuses on the interaction between *Portfolio 3* and *Portfolio Aggregate* before and after the announcement, respectively LogLik is the value of the log likelihood. SIC and AIC are the Schwarz Criterion and Akaike information criterion, respectively. CORR(12) (respectively, CORRSQ(12)) is the LM test statistic for autocorrelation up to order 12 in the standardized residuals $\frac{h_t}{\hat{\mu}_t}$ (respectively, squared standardized residuals $\frac{h_t^2}{\hat{\mu}_t^2}$) with the corresponding p-values in parentheses. ϕ is the estimated method of moments gamma parameter.

	Base Model (1)	Base Model (2)	Selected Model (1)	Selected Model (2)
ω	0.0156**	0.0490***	0.0193*	0.0787***
	(0.0093)	(0.0170)	(0.0106)	(0.0238)
$\mu_{aggregate,t-1}$	0.8653***	0.7044***	0.8622***	0.6248***
	(0.0585)	(0.0759)	(0.0640)	(0.0917)
$hl_{aggregate,t-1}$	0.0901**	0.1841***	-0.0131	0.1269*
	(0.0381)	(0.0528)	(0.0556)	(0.0551)
$hl_{2,t-1}$			0.0754	
			(0.0564)	
$hl_{3,t-1}$				0.0818*
				(0.0414)
PC_{t-1}			0.0587	0.1305**
		(0.0493)		(0.0517)
$PC_{t-1}hl_{2,t-1}$			-0.1434	
			(0.1200)	
$PC_{t-1}hl_{3,t-1}$				-0.5103***
				(0.1467)
Loglik	-423.7331	-478.4453	-423.3590	-477.8569
SIC	1.8079	2.0363	1.8450	2.0725
AIC	1.7818	2.0102	1.7927	2.02023
LB(12)	6.8608	14.0310	5.1654	15.3820
	(0.867)	(0.299)	(0.952)	(0.221)
LBSQ(12)	17.1000	13.2020	9.4054	15.1440
	(0.146)	(0.355)	(0.668)	(0.234)
$\hat{\phi}$	4.5082	4.9459	4.6926	5.1234

Notes: Robust standard errors are shown in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

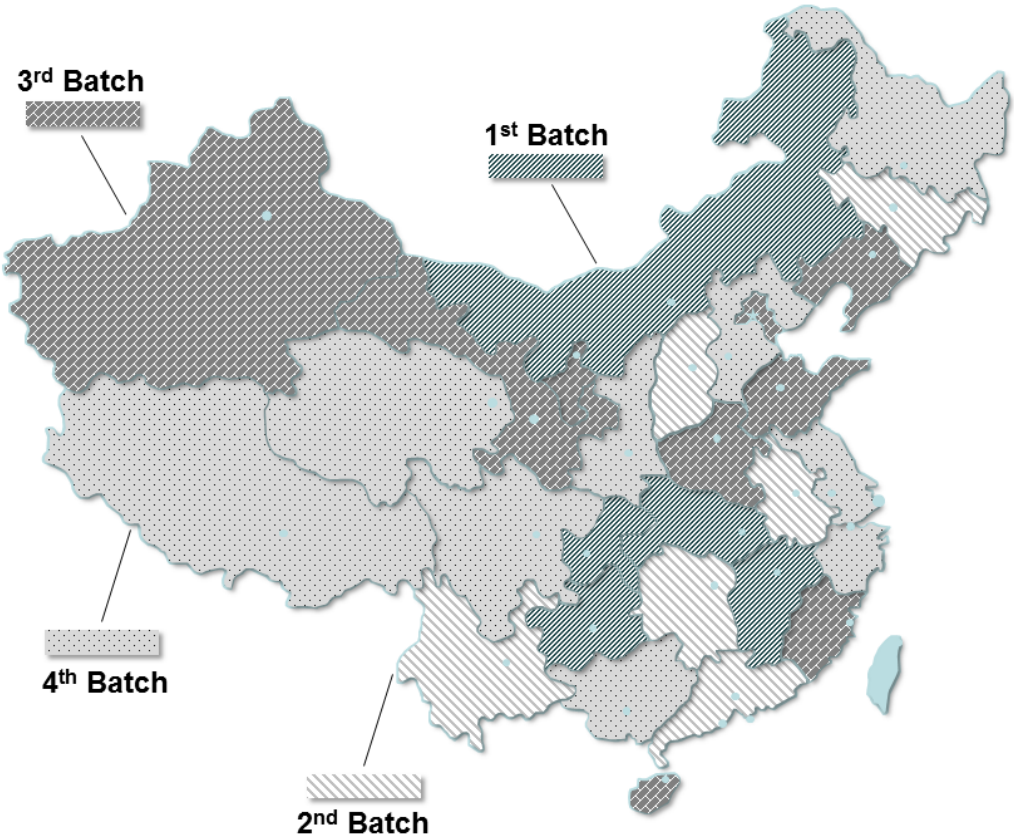

Figure 1: Geographical distribution of the first four batches. The different colours identify the different batches.

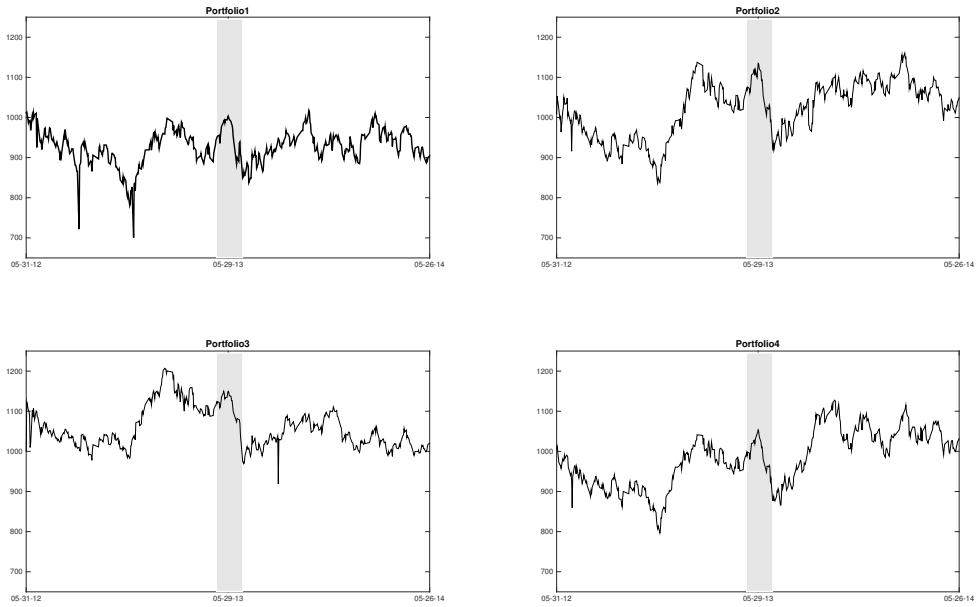

Figure 2: Synthetic Portfolio Indices, May 2012 - May 2014. The shaded area corresponds to the first announcement period, 8 May 2013 - 21 June 2013.

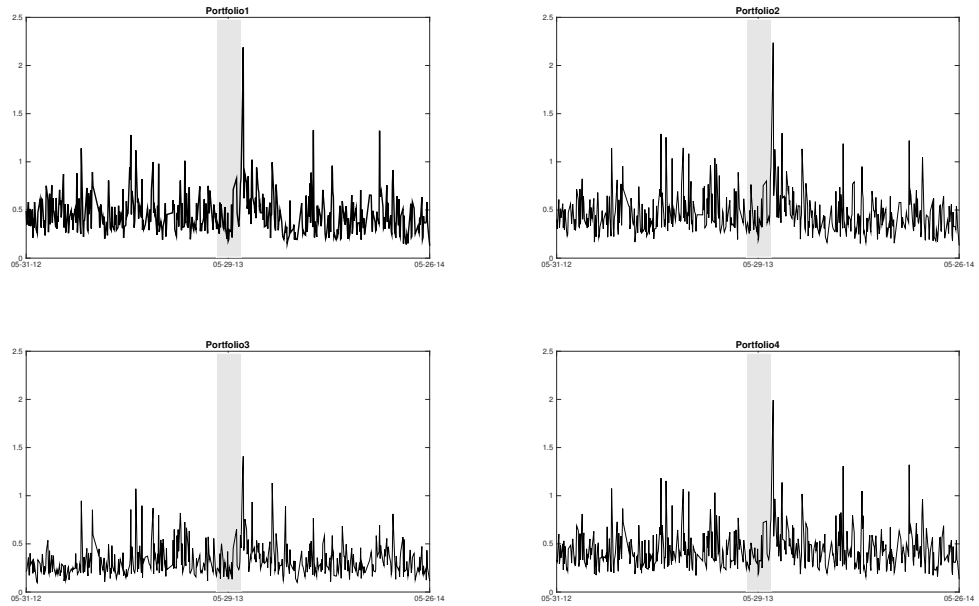

Figure 3: Time Series Plots of Annualized hl_t for the four portfolios, May 2012 - May 2014. The shaded area corresponds to the first announcement period, 8 May 2013 - 21 June 2013.

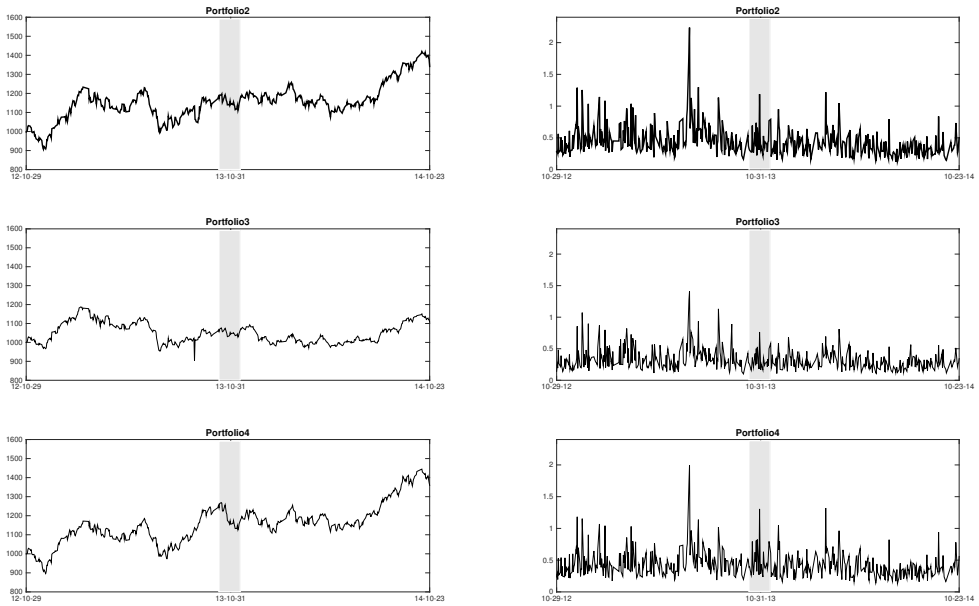

Figure 4: Synthetic Portfolio Indices (left figures) and Time Series Plots of Annualized hl_t (right figures) for $Portfolio2$, $Portfolio3$ and $Portfolio4$ at the time of the second investigation, October 2012 - October 2014. The shaded area corresponds to the second announcement period, 10 October 2013 - 20 November 2013.

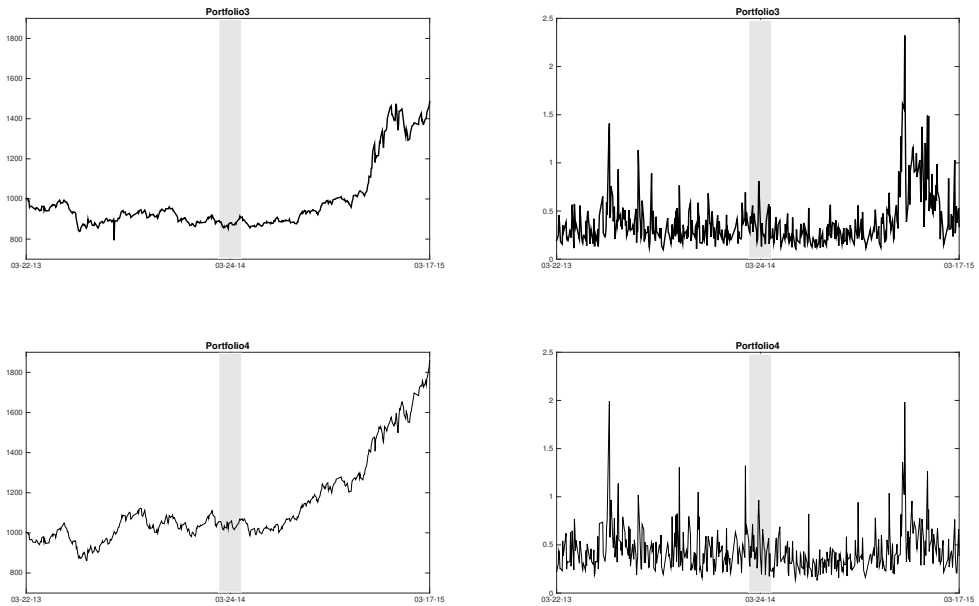

Figure 5: Synthetic Portfolio Indices (left figures) and Time Series Plots of Annualized hl_t (right figures) for $Portfolio3$ and $Portfolio4$, March 2013 - March 2015. The shaded area corresponds to the third announcement period, 3 March 2014 - 14 April 2014.

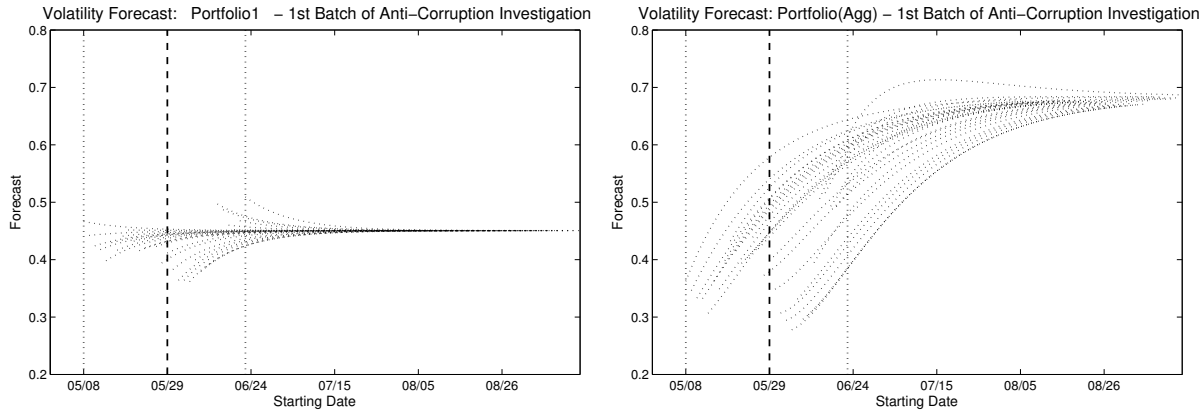

Figure 6: Dynamic volatility forecasts on *Portfolio 1* and *Aggregate*, including *Portfolio 2*, *Portfolio 3* and *Portfolio 4*, starting from 8 May 2013, and progressively moving the initial condition ahead.

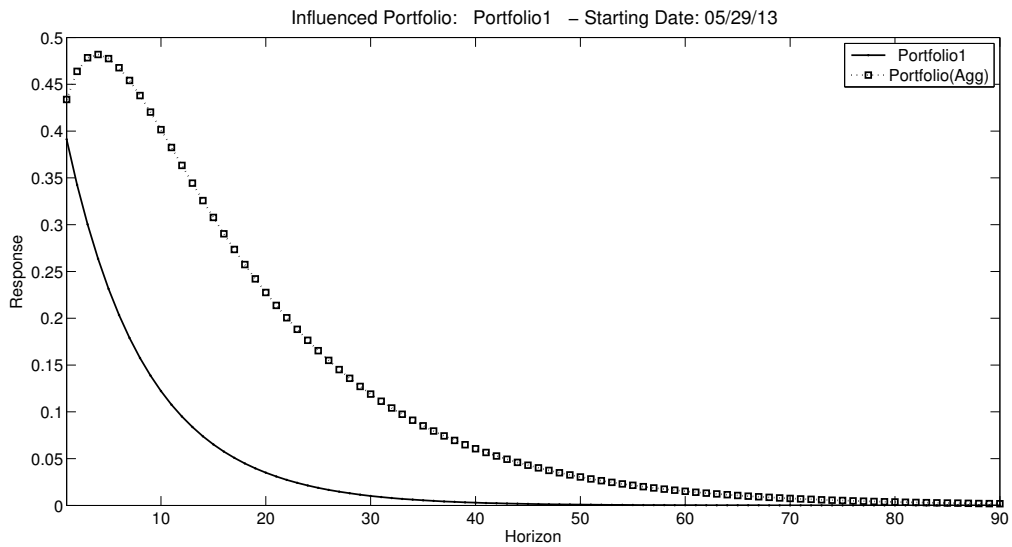

Figure 7: MEM impulse response functions of *Portfolio 1* and *Aggregate*, including *Portfolio 2*, *Portfolio 3* and *Portfolio 4* at the time of the first announcement, 29 March 2013. The originating portfolio is *Portfolio 1*.

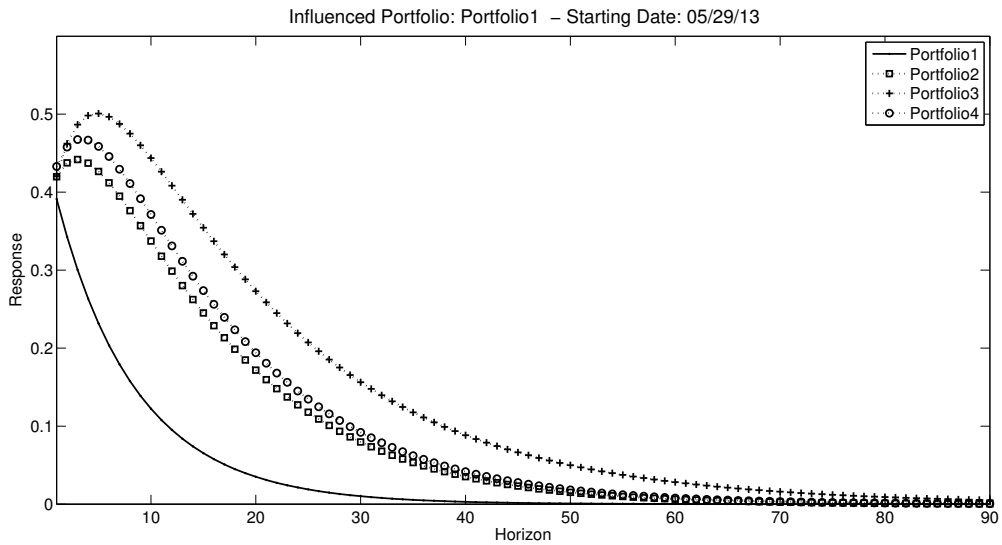

Figure 8: MEM impulse response functions of *Portfolio 1*,*Portfolio 2*, *Portfolio 3* and *Portfolio 4* at the time of the first announcement, 29 March 2013. The originating portfolio is *Portfolio 1*.

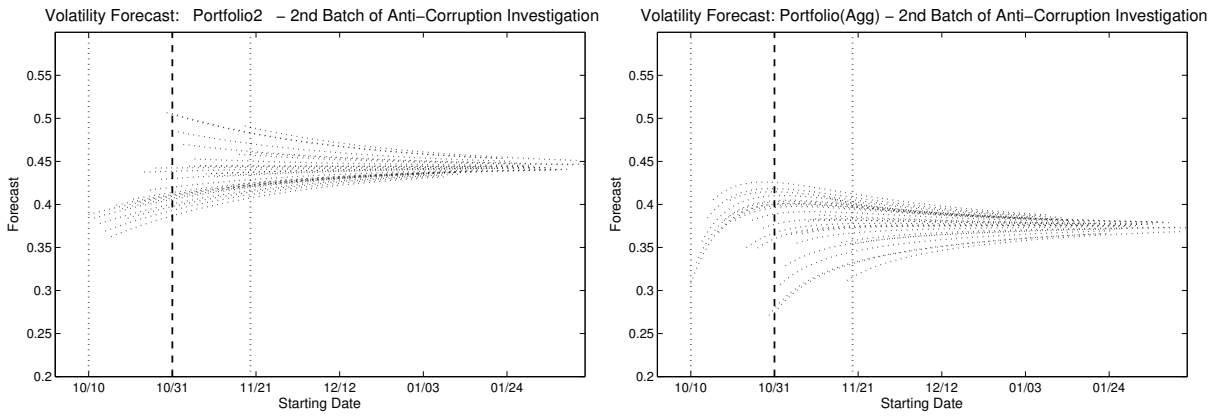

Figure 9: Dynamic volatility forecasts on *Portfolio 2* and *Aggregate*, including *Portfolio 3* and *Portfolio 4*, starting from 10 October 2013, and progressively moving the initial condition ahead.

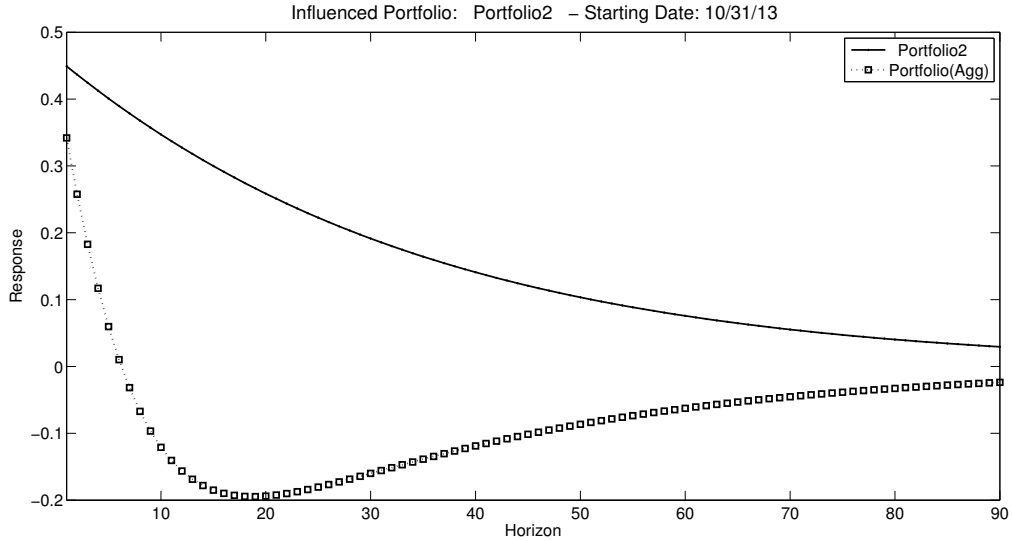

Figure 10: MEM impulse response functions of *Portfolio 2*, and *Aggregate*, including *Portfolio 3* and *Portfolio 4* at the time of the second announcement, 31 October 2013. The originating portfolio is *Portfolio 2*.

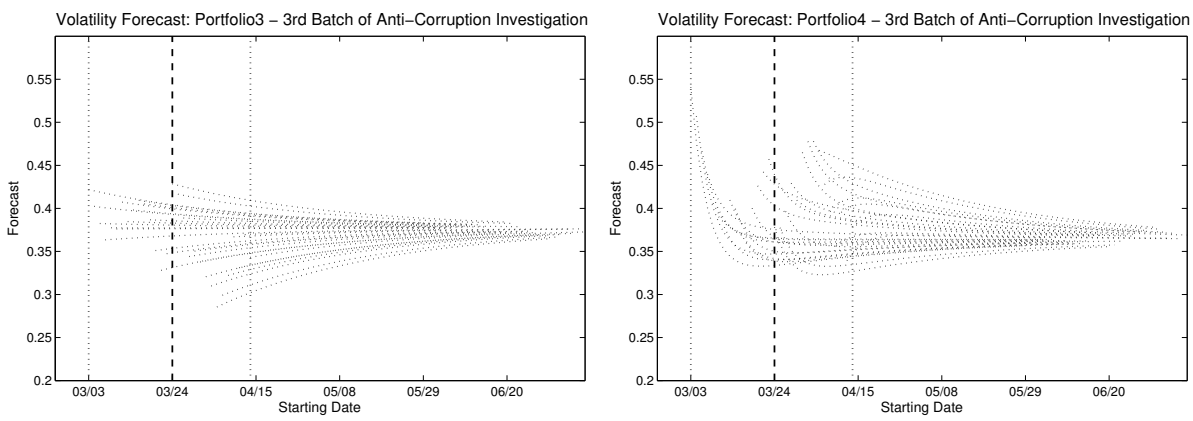

Figure 11: Dynamic volatility forecasts on *Portfolio 3* and *Portfolio 4*, starting from 3 March 2014, and progressively moving the initial condition ahead.

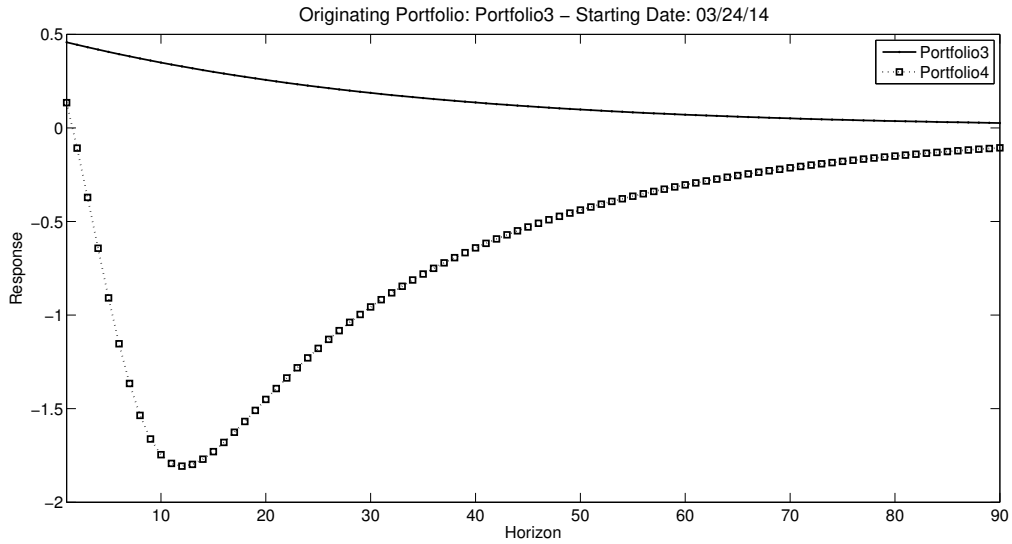

Figure 12: MEM impulse response functions of *Portfolio 3* and *Portfolio 4* at the time of the third announcement, 24 March 2014. The originating portfolio is *Portfolio 3*.