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**Highlights**

- Credit supply distortion adversely impacts corporate investment efficiency.
- Managerial forecast ability mitigates the adverse effect of credit supply distortion for non-SOEs but not for SOEs.
- Negative credit supply distortions have a greater impact on corporate investment efficiency and managerial forecast ability is important in reducing underinvestment.
- Financial stability should be properly considered within the monetary policy framework.

# How does credit market distortion affect corporate investment efficiency? The role of managerial forecast

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**Abstract**

The purpose of this paper is to study the interaction among corporate investment efficiency, credit supply distortion and managerial forecast ability in China. We provide robust evidence that credit distortion adversely affects corporate investment efficiency, while better managerial forecast ability mitigates this negative effect. Subsample analyses show that managerial forecast ability mitigates the adverse effect of credit supply distortion for non-state-owned enterprises but not for state-owned enterprises. We also find evidence that negative credit supply distortions have a greater impact on corporate investment efficiency and managerial forecast ability is particularly important in reducing underinvestment.

**Keywords:** investment efficiency; credit distortion; managerial forecast ability

**JEL classification***: G30, D81, E22, E60, G18*

## 1. Introduction

In the neo-classical framework, managers make optimal investment decisions to maximize the firm value according to the marginal Q ratio. However, firms may depart from this optimal level in practice, resulting in investment inefficiency. The existing literature focuses on the impact of firm-level factors on investment efficiency, such as the quality of financial reports, financial constraints, as well as agency costs (Biddle *et al*., 2009; Guariglia and Yang, 2016), while neglecting to examine whether distortion of external

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conditions causes corporate investment inefficiency, since corporate investment behaviour is sensitive to credit availability (Cingano *et al*., 2016). We investigate the impact of credit supply distortion on corporate investment efficiency and expect that distortion in the credit supply may induce distorted investment, and reduce investment efficiency.[1]

More importantly, firm investment decisions rely on managerial forecast for the project payoff, cash flow and product demand, as well as the external environment among others. Managers with better forecast quality make more efficient investment (Goodman *et al*., 2014). Engelhardt (2012) argues that wiser entrepreneurs with better forecast ability may predict the distorting effects of credit supply and thereby make better investment decisions during a credit expansion. However, there is a lack of empirical evidence and we intend to fill this gap. Specifically, we test whether better managerial forecast ability can mitigate the adverse impact of credit distortion on corporate investment efficiency.

We focus on the Chinese credit market, which has emerged as the world's biggest 'money printing machine' since 2009. Chinese state-owned banks dominate financial markets and banking loans serve as the key financial tool for corporate investment (Allen *et al*., 2012). However, Chinese government intervention through state-owned banks can cause credit supply distortions.[2] In addition, alternative corporate financing channels are limited. This creates an ideal laboratory for us to test the role of credit supply distortion on corporate investment decisions.

Our work is related and contributes to the studies on the impact of credit supply on corporate activities. Previous studies are either concerned with the channel through which credit shock affects corporate financing and investment by exploiting a specific event (e.g., Iyer *et al*., 2014; Cingano *et al*., 2016), or investigate the impact of a continuous credit supply cycle on corporate activities (e.g., Becker & Ivashina, 2014). However, there is a lack of literature discussing whether credit supply distortion causes corporate investment inefficiency. This paper stands as an initial attempt to examine the role of credit supply distortion on corporate investment efficiency and its relevant mechanism empirically. We find that credit supply distortion reduces corporate investment efficiency robustly.

The second contribution is that we provide new insights into corporate investment behaviour and highlight the role of managerial skills in terms of forecast ability. Although managerial forecast ability

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[1] In this paper, credit supply distortion refers to the deviation from the expected credit supply. The investment distortion (inefficiency) means the deviation from the expected firm investment.
[2] A recent example is the four trillion stimulus plan of Chinese government in 2008.

cannot be observed directly, Goodman *et al.* (2014) argue that managerial earnings forecast quality can serve as a proxy for the investment forecast ability and managers with better forecast ability can make more efficient investment. Engelhardt (2012) indicates that astute entrepreneurs with better forecast ability may recognize the distorting effect of credit policy and thereby make better investment decisions. In this paper, we intend to empirically investigate whether better managerial forecast ability can mitigate the negative effects of credit supply distortion on corporate investment efficiency.

The third contribution is that we distinguish between the performances of managers from state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). Our motivation is that most managers in SOEs are appointed by the Chinese government. On the one hand, these managers tend to cater to government policy as politicians instead of simply focusing on maximizing profit (Chen *et al*., 2006), which might lead to investment inefficiency during the credit distortion period. On the other hand, SOEs' connection to government might facilitate their ability to obtain credit support from state-owned banks (Allen *et al*., 2012). Our empirical results document that credit supply distortion decreases the investment efficiency for both SOEs and non-SOEs, while the managerial forecast ability only plays an effective role to mitigate the negative impact of credit supply distortion in non-SOEs.

The rest of the paper is organized as follows. We present the data and methodology in Section 2. Section 3 discusses the empirical results along with robustness tests and extension analyses. Section 4 concludes.

## 2. Data and Methodology

### *2.1. Sample selection*

We study quarterly investment performance of publicly listed companies on the Shanghai and Shenzhen Stock Exchanges in China, excluding Special Treatment (ST)[3] companies and financial companies. Quarterly data help facilitate the exploration of the short-term macroeconomic impacts on firm investment behavior and strengthen the statistic power (Duchin *et al*., 2010; Gulen and Ion, 2016; Becker and Ivashina, 2014; Wang *et al*., 2014). The firm-level accounting data and managerial earnings forecast data are retrieved from the WIND financial database. The credit-related data are gathered from the People's Bank of China (PBOC) and the National Bureau of Statistics (NBS). The sample spans from

[3] ST companies are companies with financial troubles or in abnormal situations.

2003Q1 to 2015Q4.

### *2.2. Methodology and variables*

To investigate the impact of credit supply distortion on corporate investment efficiency and how managerial forecast ability affects their relation, we estimate the following equations:

$$Invest\_Eff_{i,t} = \alpha_0 + \alpha_1 Distortion_t + \alpha_2 Control_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

$$Invest\_Eff_{i,t} = \beta_0 + \beta_1 Distortion_t + \beta_2 Distortion_t * Forecast_i + \beta_3 Control_{i,t-1} + \sigma_{i,t} \quad (2)$$

*Invest_Eff* is the corporate investment efficiency, which is obtained from the expected investment model (Biddle *et al*., 2009, Gomariz and Ballesta, 2014 and Goodman *et al*., 2014). We firstly calculate the residual $\omega_{i,t}$ by regressing the lagged growth rate of sales on investment[4] cross-sectionally for each year and industry.[5] The intuition of the expected investment model is that a firm's investment is a function of its growth opportunity that is measured by the sales growth rate,[6] while the predicted value and residual of expected investment model proxy expected investment and unexpected (or abnormal) investment, respectively. A positive residual means overinvestment and a negative value means underinvestment. Therefore, the residuals measure investment inefficiency, increasing with the absolute value of the residuals. Then we multiply the absolute value of the residual by (-1) to get the investment efficiency denoted by *Invest_Eff*. The investment efficiency increases with the value of *Invest_Eff*.

*Distortion* measures the credit supply distortion. Inspired by Povel *et al*. (2016) and Mendoza and Terrones (2008), we get the residual $e_t$ from regressing the logarithm of real credit per capita[7] on the time trend and then set *Distortion* as the absolute value of $e_t/\sigma(e_t)$, where $\sigma(e_t)$ is the standard deviation of $e_t$. Credit supply distortion increases with the value of *Distortion.*

We construct three proxies for *Forecast*. *Forecast* measures the managerial forecast ability based on the managerial earnings forecast information. Inspired by Goodman *et al*. (2014) and Hilary *et al*. (2014), we use forecast accuracy and forecast consistency as well as their mean value to measure the managerial forecast ability. We firstly compute the managerial forecast error which is the difference between the forecasted net profit growth rate and the actual value.[8] As a smaller absolute value of forecast errors

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[4] Investment = capital expenditure / total assets in the last period.
[5] At least 20 available observations are required.
[6] We also use the Tobin's Q instead of sales growth as the proxy for growth opportunity in the robustness test.
[7] The logarithm of real credit per capita = Ln (real credit adjusted by the CPI in 2000Q1 / total population size). Here, the population census data are of annual frequency, while the credit data are quarterly, so we decompose the population data into quarterly frequency with the quadratic-match average method. Results are also consistent if we do not adjust for the population size.
[8] In the US market, Hilary *et al*. (2014) and Goodman *et al*. (2014) measure the forecast ability by comparing the forecasted

means higher forecast accuracy (Goodman *et al*., 2014), we define managerial forecast accuracy (*Facc*) as an indicator variable that equals one if the average absolute value of a firm's managerial forecast errors over the whole sample period is less than its industry median, otherwise zero. Similarly, a smaller variation of forecast errors means larger forecast consistency (Hilary *et al*., 2014), we define managerial forecast consistency (*Fcon*) as an indicator variable that equals one if the standard deviation of a firm's managerial forecast errors over the sample period is less than its industry median, otherwise zero. The third proxy for managerial forecast ability is denoted as *Facccon* which takes on the mean value of *Facc* and *Fcon*. These three proxies, *Facc*, *Fcon* and *Facccon* are firm-level time-invariant variables.

*Control* is a vector of control variables that may influence corporate investment behavior. These variables include sales divided by total assets (*Sales*), net cash flow from operating divided by total assets (*Cash*), total liabilities divided by total assets (*Leverage*), net income divided by total assets (*ROA*), overhead expenses divided by total assets (*Agency*) (Huang *et al*., 2011), the ratio of fixed assets to total assets (*Tangibility*), financial constraints (*SA index*) (Hadlock and Pierce, 2010), market-to-book asset value (*MTB*), inventory divided by total assets (*Inventory*), accounts payable divided by total assets (*Payable*).[9] We lag these control variables by one period and winsorize them at the 1% and 99% levels to mitigate any undue influences of outliers. We estimate the regression using the fixed-effect model with firm, year and quarter fixed effects. We cluster the standard errors at the firm-level to adjust for the heteroskedasticity within firms. We do not include Forecast as an independent variable in the baseline regression because the firm fixed effect absorbs this time-invariant variable. The similar identification can be found in Duchin *et al*., (2010) and Cavallo *et al.* (2013). We also construct time-variant proxies for managerial forecast ability in the robustness check and we include both this variable and its interaction term in the regression.

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EPS with the actual EPS. However, listed companies in China only disclose the forecasted net profit and the growth rate of net profit but do not directly disclose forecasted EPS. We notice that in our sample, there are more companies choosing to disclose forecasted net profit growth rate rather than net profit. For the sake of consistency, in our analysis, we select the net profit growth rate to construct our proxies. The forecast-related data are retrieved from the WIND database.

[9] The summary statistics for all the variables are shown in the Appendix.

## 3. Empirical Results

### *3.1. Baseline model results*

Column (1) of Table 1 are the baseline results for Equations (1). As expected, the key independent variable *Distortion* is negatively associated with investment efficiency and statistically significant at the 1% level, indicating that the credit supply distortion decreases corporate investment efficiency. Specifically, the coefficient of *Distortion* in column (1) is –0.002, implying that as credit supply distortion increases one standard deviation, corporate investment efficiency decreases 0.001[10] units on average, which is 5.5% over the sample mean.

Columns (2) – (4) show the results for Equations (2) with various proxies for managerial forecast ability. The interaction terms between managerial forecast ability and credit supply distortion carry positive signs and are statistically significant at the 1% level. This finding indicates that credit supply distortions hamper investment efficiency to a lesser extent in those companies whose managers have better forecast ability.

### *3.2. Robustness tests*

In Table 2 we implement several robustness tests to provide additional support for our baseline model findings. Firstly, we only include firms with at least 20 and 30 managerial forecast observations to ensure enough observations when constructing measurements for managerial forecast ability. Secondly, we try an alternative measurement of credit supply distortion (*Distortion_2*) by using the absolute value of the deviation from the long-run trend in the logarithm of real credit per capita with the Hodrick-Prescott (HP) filter (Panel B). Thirdly, to mitigate the concern that managerial forecast ability may vary with time, we construct time-variant measurements for managerial forecast ability (Panel C). Specifically, we define the time-variant managerial forecast accuracy (*Facc_2*) as an indicator variable that equals one if the average absolute value of the managerial forecast errors in a given year is below its industry median, otherwise zero. The time-variant managerial forecast consistency (*Fcon_2*) is also an indicator variable that equals one if the standard deviation of the managerial forecast errors in a given year is below its industry median, otherwise zero. Similarly, *Facccon_2* is the mean value of *Facc_2* and *Fcon_2*. Finally, we estimate the expected investment model with Tobin's Q instead of sales growth as the proxy for growth opportunity and

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[10] 0.001=0.002*0.584 where 0.584 is the standard deviation of *Distortion*.

the new investment efficiency is denoted as *Invest_Eff_2* (Panel D).[11] All the results are consistent with those from the baseline model.

### *3.3. Extension analyses*

In Table 3, we conduct some extension analyses to examine the roles of ownership structure, the split-share structure reform and the financial crisis. We also study the impact of different kinds of credit supply distortion on investment inefficiency. In Panel A we separate the firms into SOEs and non-SOEs, as the effects of government credit across different levels of the supply chain could be distinct (Huang *et al.*, 2011; Ru, 2017). The results show that the credit supply distortion decreases the corporate investment efficiency for both SOEs and non-SOEs while the interaction terms are not statistically significant for SOEs. This may suggest that many SOE managers are appointed politically and their social and political goals undermine corporate interests (Chen *et al.*, 2006).

In Panel B, we divide the sample into periods before the split-share structure reform (2003-2007) and after the split-share structure reform (2008-2015), as the Chinese government launched the split-share structure reform during 2005-2007 and most firms finished their reform in the end of 2007 (Liao *et al.*, 2014). The results show that the baseline conclusions mainly apply to the post-reform subsample, which implies that after the split-share reform, the Chinese stock market is more sensitive to monetary policy changes.

In Panel C, we divide the sample into crisis and non-crisis subperiods and re-run the regressions. We define the years 2008-2013 as the financial crisis period, which covers both the US subprime crisis and the European debt crisis. It is evident that during the financial crisis period, the credit distortion impairs corporate investment efficiency. However, there is little evidence that the managerial forecast ability can mitigate the negative effects of credit distortion in this particular subsample. As a comparison, we see that, to a certain extent, managerial forecast ability still plays a role during the non-crisis period.

In Panel D, we investigate the effect of political connections since political connections help firm access to bank loans (Cumming *et al.*, 2016). We define a firm as with political connections if at least one of its senior managers (including directors) is or was government official, the People's Congress (PC) member or the Chinese People's Political Consultative Conference (CPPCC) member. The credit supply

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[11] In an untabulated table, we use the analyst forecasted earnings instead of the firm's actual earnings as the benchmark to construct the managerial forecast ability to mitigate the concern that managers with lower integrity may manipulate the earnings (Chen *et al.*, 2013) to cater to their forecast.

distortion decreases investment efficiency for both subsamples, but only statistically significant for firms without political connections. However, the managerial forecast ability plays a mitigating role in the politically connected firms. These results are consistent with Cumming *et al.* (2016) that political connections mitigate the financial constraint on the investment.[12]

In Panel E, we analyze cases when positive and negative credit supply distortions are taken into account separately. We expect that positive credit distortions (*Distortion_P*) promote corporate overinvestment and negative credit distortions (*Distortion_N*) cause corporate underinvestment. The dependent variable in columns (1) – (3) is *Overinvestment* which takes on the value of $\omega_{i,t}$ if $\omega_{i,t}$ is positive and 0 otherwise. The main independent variable *Distortion_P* takes on the value of $e_t/\sigma(e_t)$ if $e_t$ is positive and 0 otherwise. In columns (4) – (6), the dependent variable is *Underinvestment* which takes on the absolute value of $\omega_{i,t}$ if $\omega_{i,t}$ is negative and 0 otherwise. The negative distortion *Distortion_N* takes on the absolute value of $e_t/\sigma(e_t)$ if $e_t$ is negative and 0 otherwise. We find that both coefficients in front of *Distortion_P* and *Distortion_N* are positive, but not statistically significant for *Distortion_P*. The coefficients of the interaction terms are negative, but only statistically significant for *Distortion_N*Forecast*. These results show that managerial forecast ability is particularly important in terms of helping reduce underinvestment.

## 4. Conclusions

Credit supply plays an important role in corporation financing decisions and it also sends out key signals to guide companies on investment decisions making. Corporate investment efficiencies also hinge upon managerial forecast accuracy and consistency. In this paper, we investigate how credit distortion affects corporate investment efficiency and the role played by managerial forecast ability. Our empirical analyses document that credit distortions adversely affect corporate investment efficiency, especially in the periods after the split-share structure reform and during the financial crisis, while better managerial forecast ability mitigates this negative effect but only for non-SOEs. Additionally, our findings indicate a greater impact from negative credit supply distortions on corporate investment efficiency and underscore the importance of managerial forecast ability in reducing underinvestment. Most importantly, our results

[12] The information on political connections is collected from the CSMAR Financial Database and it started from 2008, resulting in the smaller sample size compared to those in the baseline results.

demonstrate that changes in credit supply within the financial system inevitably affect the real economy. From the policymakers' point of view, financial stability should be properly considered within the monetary policy framework given the importance of credit supply.

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**Table 1. Baseline results**

This table reports the results for Equations (1) and (2). The dependent variable is investment efficiency (*Invest_Eff*). *Distortion* is the proxy for credit supply distortion. *Facc, Fcon and Facccon* are proxies for managerial forecast ability. Please refer to Subsection 2.2 for variable definitions. The year and quarter effect as well as the firm fixed effect are controlled for in all regressions. Robust t-statistics adjusted for firm-level clustering are reported in parentheses. $^{***}$, $^{**}$ and $^{*}$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| | Dependent Variable = Investment Efficiency (*Invest_Eff*) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Distortion* | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| | (-3.92) | (-4.12) | (-4.00) | (-4.15) |
| *Distortion*Facc* | | 0.001** | | |
| | | (2.04) | | |
| *Distortion*Fcon* | | | 0.001** | |
| | | | (2.09) | |
| *Distortion*Facccon* | | | | 0.001** |
| | | | | (2.14) |
| *Sales* | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| | (2.82) | (2.79) | (2.83) | (2.78) |
| *Cash* | -0.009*** | -0.009*** | -0.009*** | -0.009*** |
| | (-3.11) | (-3.20) | (-3.09) | (-3.19) |
| *Leverage* | -0.002 | -0.003 | -0.002 | -0.002 |
| | (-1.22) | (-1.26) | (-1.17) | (-1.25) |
| *ROA* | 0.015 | 0.016 | 0.016 | 0.016 |
| | (1.47) | (1.47) | (1.50) | (1.48) |
| *Agency* | 0.047** | 0.045* | 0.041* | 0.045* |
| | (2.01) | (1.92) | (1.74) | (1.92) |
| *Tangibility* | 0.004 | 0.004 | 0.004* | 0.004 |
| | (1.61) | (1.62) | (1.65) | (1.63) |
| *SA index* | -0.014*** | -0.014*** | -0.014*** | -0.014*** |
| | (-10.99) | (-10.94) | (-10.83) | (-10.96) |
| *MTB* | -0.001*** | -0.001*** | -0.002*** | -0.001*** |
| | (-8.51) | (-8.57) | (-8.84) | (-8.58) |
| *Inventory* | 0.015*** | 0.016*** | 0.015*** | 0.016*** |
| | (6.64) | (6.76) | (6.66) | (6.76) |
| *Payable* | -0.001 | -0.001 | -0.001 | -0.001 |
| | (-0.18) | (-0.27) | (-0.30) | (-0.26) |
| *Constant* | -0.042*** | -0.042*** | -0.042*** | -0.042*** |
| | (-16.23) | (-16.17) | (-16.01) | (-16.18) |
| *Year & Quarter Effect* | Yes | Yes | Yes | Yes |
| *Firm Fixed Effect* | Yes | Yes | Yes | Yes |
| *Cluster by firm* | Yes | Yes | Yes | Yes |
| *Observations* | 62,403 | 60,168 | 60,168 | 60,168 |
| *Adj. $R^2$* | 0.057 | 0.057 | 0.058 | 0.057 |
| *Number of Firms* | 2,104 | 1,924 | 1,924 | 1,924 |

## Table 2. Robustness tests

This table reports the robustness tests of Equations (1) and (2). Panel A only includes firms with at least 20 managerial forecast observations in columns (1) - (3) and at least 30 managerial forecast observations in columns (4) - (6). Panel B reports the results with alternative measurement for credit supply distortion (*Distortion_2*). Panel C shows the results with alternative measurements for managerial forecast ability (*Facc_2*, *Fcon_2* and *Facccon_2*). Panel D reports the results with alternative measurement for investment efficiency (*Invest_Eff_2*). The definitions of *Distortion_2*, *Facc_2*, *Fcon_2*, *Facccon_2* and *Invest_Eff_2* are as shown in Subsection 3.2. We include but do not report all the control variables and fixed effects in this table for brevity purpose. Robust t-statistics adjusted for firm-level clustering are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| **Panel A** | Dependent Variable = Investment Efficiency (Invest_Eff) | | | | | |
|---|---|---|---|---|---|---|
| | Forecast Observations >=20 | | | Forecast Observations >=30 | | |
| *Forecast=* | *Facc* | *Fcon* | *Facccon* | *Facc* | *Fcon* | *Facccon* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Distortion* | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| | (-3.99) | (-3.89) | (-4.02) | (-3.52) | (-3.40) | (-3.55) |
| *Distortion*Forecast* | 0.001** | 0.001** | 0.001** | 0.001* | 0.001* | 0.001* |
| | (2.08) | (2.14) | (2.17) | (1.77) | (1.87) | (1.86) |
| *Observations* | 59,157 | 59,157 | 59,157 | 47,759 | 47,759 | 47,759 |
| *Adj.* $R^2$ | 0.058 | 0.058 | 0.058 | 0.060 | 0.060 | 0.060 |
| *Number of Firms* | 1,753 | 1,753 | 1,753 | 1,131 | 1,131 | 1,131 |

| **Panel B** | Dependent Variable = Investment Efficiency (*Invest_Eff*) | | | |
|---|---|---|---|---|
| *Forecast=* | | *Facc* | *Fcon* | *Facccon* |
| | (1) | (2) | (3) | (4) |
| *Distortion_2* | -0.034*** | -0.043*** | -0.042*** | -0.044*** |
| | (-2.91) | (-3.22) | (-3.03) | (-3.22) |
| *Distortion_2*Forecast* | | 0.024** | 0.023** | 0.025** |
| | | (2.22) | (2.06) | (2.23) |
| *Observations* | 62,403 | 60,168 | 60,168 | 60,168 |
| *Adj.* $R^2$ | 0.057 | 0.057 | 0.058 | 0.057 |
| *Number of Firms* | 2,104 | 1,924 | 1,924 | 1,924 |

| **Panel C** | Dependent Variable = Investment Efficiency (*Invest_Eff*) | | |
|---|---|---|---|
| *Forecast=* | *Facc_2* | *Fcon_2* | *Facccon_2* |
| | (1) | (2) | (3) |
| *Distortion* | -0.003*** | -0.002* | -0.002** |
| | (-3.34) | (-1.89) | (-2.16) |
| *Forecast* | 0.001*** | 0.002*** | 0.002*** |
| | (2.70) | (3.28) | (2.88) |
| *Distortion*Forecast* | 0.002*** | 0.001* | 0.002** |
| | (2.80) | (1.75) | (2.33) |
| *Observations* | 31,101 | 31,101 | 31,101 |
| *Adj.* $R^2$ | 0.057 | 0.055 | 0.056 |
| *Number of Firms* | 1,816 | 1,816 | 1,816 |

| **Panel D** | Dependent Variable = Investment Efficiency (*Invest_Eff_2*) | | | |
|---|---|---|---|---|
| *Forecast=* | | *Facc* | *Fcon* | *Facccon* |
| | (5) | (6) | (7) | (8) |
| *Distortion* | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| | (-3.35) | (-3.64) | (-3.54) | (-3.69) |

| | | | | |
|---|---|---|---|---|
| *Distortion*Forecast* | | 0.001** | 0.001** | 0.001** |
| | | (2.04) | (2.19) | (2.14) |
| *Observations* | 63,317 | 61,017 | 61,017 | 61,017 |
| *Adj. $R^2$* | 0.059 | 0.060 | 0.061 | 0.060 |
| *Number of Firms* | 2,147 | 1,930 | 1,930 | 1,930 |

**Table 3. Extension analyses**

This table reports the subsample test results of Equation (2). Panel A reports the results for SOEs and non-SOEs. Panel B shows the results before and after the split-share structure reform. Panel C reports the results for the financial crisis and non-crisis periods. Panel D shows the impacts of positive or negative credit supply distortions on investment inefficiency. Columns (1) – (3) in Panel D examine the impacts of positive credit supply distortion on corporate overinvestment. Columns (4) – (6) in Panel D report the impacts of negative credit supply distortion on corporate underinvestment. The definitions of *Overinvestment, Underinvestment, Distortion_P and Distortion_N* are given in Subsection 3.3. We include but do not report all the control variables and fixed effects in this table for brevity purpose. Robust t-statistics adjusted for firm-level clustering are reported in parentheses. $^{***}$, $^{**}$ and $^{*}$ indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| **Panel A** | Dependent Variable = Investment Efficiency (*Invest_Eff*) | | | | | |
|---|---|---|---|---|---|---|
| | Non-SOE | | | SOE | | |
| *Forecast=* | *Facc* | *Fcon* | *Facccon* | *Facc* | *Fcon* | *Facccon* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Distortion* | -0.003$^{**}$ | -0.003$^{***}$ | -0.004$^{***}$ | -0.002$^{**}$ | -0.001$^{*}$ | -0.001$^{**}$ |
| | (-3.74) | (-3.99) | (-3.99) | (-2.08) | (-1.84) | (-1.98) |
| *Distortion$^{*}$Forecast* | 0.001$^{**}$ | 0.002$^{***}$ | 0.002$^{**}$ | 0.000 | -0.000 | 0.000 |
| | (1.96) | (2.61) | (2.39) | (0.35) | (-0.16) | (0.13) |
| *Observations* | 32,271 | 32,271 | 32,271 | 28,060 | 28,060 | 28,060 |
| *Adj. $R^2$* | 0.057 | 0.058 | 0.057 | 0.059 | 0.060 | 0.059 |
| *Number of Firms* | 1,432 | 1,432 | 1,432 | 733 | 733 | 733 |

| **Panel B** | Dependent Variable = Investment Efficiency (*Invest_Eff*) | | | | | |
|---|---|---|---|---|---|---|
| | Before Reform | | | After Reform | | |
| *Forecast=* | *Facc* | *Fcon* | *Facccon* | *Facc* | *Fcon* | *Facccon* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Distortion* | -0.001 | -0.002$^{*}$ | -0.002 | -0.003$^{***}$ | -0.003$^{***}$ | -0.003$^{***}$ |
| | (-1.44) | (-1.65) | (-1.59) | (-4.40) | (-4.22) | (-4.43) |
| *Distortion$^{*}$Forecast* | 0.001 | 0.002 | 0.002 | 0.001$^{*}$ | 0.001$^{*}$ | 0.001$^{*}$ |
| | (1.15) | (1.45) | (1.38) | (1.86) | (1.85) | (1.92) |
| *Observations* | 13,280 | 13,280 | 13,280 | 46,888 | 46,888 | 46,888 |
| *Adj. $R^2$* | 0.058 | 0.057 | 0.058 | 0.047 | 0.048 | 0.047 |
| *Number of Firms* | 883 | 883 | 883 | 1,923 | 1,923 | 1,923 |

| **Panel C** | Dependent Variable = Investment Efficiency (*Invest_Eff*) |
|---|---|

| | Non-crisis | | | During crisis | | |
|---|---|---|---|---|---|---|
| *Forecast=* | *Facc* | *Fcon* | *Facccon* | *Facc* | *Fcon* | *Facccon* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Distortion* | -0.001 | -0.001 | -0.001 | -0.002*** | -0.002** | -0.002*** |
| | (-1.23) | (-1.55) | (-1.48) | (-2.85) | (-2.56) | (-2.85) |
| *Distortion*Forecast* | 0.001 | 0.002* | 0.002* | 0.001 | 0.001 | 0.001 |
| | (1.31) | (1.90) | (1.74) | (1.60) | (1.60) | (1.62) |
| *Observations* | 27,990 | 27,990 | 27,990 | 32,178 | 32,178 | 32,178 |
| *Adj.* $R^2$ | 0.065 | 0.065 | 0.065 | 0.048 | 0.048 | 0.048 |
| *Number of Firms* | 1,922 | 1,922 | 1,922 | 1,775 | 1,775 | 1,775 |

| **Panel D** | Dependent Variable = Investment Efficiency (*Invest_Eff*) | | | | | |
|---|---|---|---|---|---|---|
| | Political Connection | | | No Political Connection | | |
| *Forecast=* | *FaccD* | *FconD* | *Facccon* | *FaccD* | *FconD* | *Facccon* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Distortion* | -0.002 | -0.002 | -0.002 | -0.006*** | -0.006** | -0.006*** |
| | (-1.21) | (-1.04) | (-1.15) | (-2.63) | (-2.58) | (-2.60) |
| *Distortion*Forecast* | 0.003** | 0.002* | 0.002* | 0.002 | 0.002 | 0.002 |
| | (1.99) | (1.73) | (1.94) | (1.22) | (1.03) | (1.16) |
| *Observations* | 10,180 | 10,180 | 10,180 | 7,371 | 7,371 | 7,371 |
| *Adj.* $R^2$ | 0.048 | 0.047 | 0.047 | 0.048 | 0.048 | 0.048 |
| *Number of Firms* | 560 | 560 | 560 | 516 | 516 | 516 |

| **Panel E** | Dependent Variable = *Overinvestment* | | | | Dependent Variable = *Underinvestment* | | |
|---|---|---|---|---|---|---|---|
| *Forecast=* | *Facc* | *Fcon* | *Facccon* | *Forecast=* | *Facc* | *Fcon* | *Facccon* |
| | (1) | (2) | (3) | | (4) | (5) | (6) |
| *Distortion_P* | 0.001 | 0.001 | 0.001 | *Distortion_N* | 0.002*** | 0.002*** | 0.002*** |
| | (1.51) | (1.13) | (1.36) | | (3.84) | (3.53) | (3.75) |
| *Distortion_P*Forecast* | -0.001 | -0.000 | -0.001 | *Distortion_N*Forecast* | -0.001*** | -0.001 | -0.001** |
| | (-1.56) | (-0.74) | (-1.13) | | (-2.65) | (-1.64) | (-2.24) |
| *Observations* | 60,168 | 60,168 | 60,168 | *Observations* | 60,168 | 60,168 | 60,168 |
| *Adj.* $R^2$ | 0.027 | 0.027 | 0.026 | *Adj.* $R^2$ | 0.044 | 0.043 | 0.043 |
| *Number of Firms* | 1,924 | 1,924 | 1,924 | *Number of Firms* | 1,924 | 1,924 | 1,924 |

**Appendix. Summary statistics**

| Variable | Mean | Median | Std dev | Min | Max |
|---|---|---|---|---|---|
| *Invest_Eff* | -0.021 | -0.013 | 0.029 | -0.241 | 0.000 |
| *Distortion* | 0.774 | 0.591 | 0.604 | 0.004 | 2.351 |
| *Facc* | 0.485 | 0.000 | 0.500 | 0.000 | 1.000 |
| *Fcon* | 0.495 | 0.000 | 0.500 | 0.000 | 1.000 |
| *Facccon* | 0.490 | 0.500 | 0.485 | 0.000 | 1.000 |
| *Sales* | 0.184 | 0.142 | 0.156 | 0.001 | 0.895 |
| *Cash* | 0.012 | 0.010 | 0.047 | -0.145 | 0.177 |
| *Leverage* | 0.467 | 0.471 | 0.219 | 0.045 | 1.000 |
| *ROA* | 0.010 | 0.009 | 0.022 | -0.085 | 0.093 |
| *Agency* | 0.013 | 0.011 | 0.010 | 0.001 | 0.063 |
| *Tangibility* | 0.301 | 0.268 | 0.199 | 0.003 | 0.816 |
| *SA index* | -2.102 | -2.065 | 0.638 | -3.574 | -0.669 |
| *MTB* | 2.608 | 1.971 | 2.024 | 0.898 | 13.575 |
| *Inventory* | 0.174 | 0.135 | 0.158 | 0.001 | 0.803 |
| *Payable* | 0.091 | 0.071 | 0.075 | 0.002 | 0.385 |
| *Invest_Eff_2* | -0.022 | -0.013 | 0.030 | -0.247 | 0.000 |
| *Distortion_2* | 0.024 | 0.014 | 0.026 | 0.000 | 0.087 |
| *Facc_2* | 0.473 | 0.000 | 0.499 | 0.000 | 1.000 |
| *Fcon_2* | 0.493 | 0.000 | 0.500 | 0.000 | 1.000 |
| *Facccon_2* | 0.483 | 0.500 | 0.450 | 0.000 | 1.000 |
| *Overinvestment* | 0.011 | 0.000 | 0.029 | 0.000 | 0.241 |
| *Underinvestment* | 0.007 | 0.000 | 0.013 | 0.000 | 0.165 |
| *Distortion_P* | 0.399 | 0.089 | 0.543 | 0.000 | 2.034 |
| *Distortion_N* | 0.375 | 0.000 | 0.608 | 0.000 | 2.351 |