Revisiting the Investment Regressions: State-owned Firms vs. Private Firms in China

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Abstract

The investment regression on a sample of Chinese listed firms shows that there is a significant correlation between investment rate and cash flow ratio after conditioning on average Q. This is true for both state-owned firms and private firms, which are conventionally considered to have different financial conditions. As noted by Cooper and Ejarque (2003), the violation of the constant-returns-to-scale assumption creates a wedge between average Q and marginal Q, and can lead to a spurious cash effect in the investment regression even when there are no financial frictions. Following their argument, this paper examines the investment regression results of the Chinese firms by estimating a standard Hayashi's (1982) model which allows for decreasing returns to scale. The estimation results suggest that despite the decreasing returns to scale of capital, the presence of financial constraints brings the standard capital adjustment model closer to the data moments of both state-owned and private firms in China.

1 Introdution

The Q theory of investment predicts that average Q, equal to marginal Q under the assumption of constant returns to scale of capital and a quadratic capital adjustment cost, is a sufficient statistic for investment in a perfect capital market. In this case, investment rates change one-for-one with average Q, which is measured by a firm's market value over the replacement cost of its capital stock. However, empirical examinations usually find that when regressing investment rate on average Q and cash flow ratio, the effect of cash flow ratio is significant and positive, while the effect of average Q is negligible. Many researchers interpret the positive investment-cash flow sensitivity as evidence of financial frictions, though other researchers challenge this interpretation (Erickson and Whited, 2000; Gomes, 2001; Cooper and Ejarque, 2003; Alti, 2003; Abel and Eberly, 2011). One argument is that the violation of the constant-returns-to-scale assumption can create a wedge between average Q and marginal Q. This wedge, rather than the presence of financial frictions, explains the observed cash effect in the investment regression (Cooper and Ejarque, 2003).

In this paper, I revisit this problem using a sample of Chinese publicly listed firms. Consistent with the empirical findings in the literature, the investment regressions suggest that investment rate is positively correlated with cash flow ratio after conditioning on average Q. Moreover, the effect of average Q on investment rate is small and not significant. I also run the investment regression on the subsamples of state-owned firms(SOE) and private firms(PE) and get similar results.

To understand whether financial frictions are necessary to explain the observed investment-cash flow sensitivity for the Chinese firms, I estimate two cases of a capital adjustment model as Hayashi (1982) with the assumption of decreasing returns to scale. The two cases are different in terms of the presence of a stark financial constraint that restricts the firm from borrowing. This means firms cannot invest more than their internal funds. The estimation is performed by targeting at the investment regression coefficients and some other moments that describe the Chinese sample.

The estimation results suggest that among the two cases, the model with financial constraints generates the simulated moments that are closer to the observed ones. Particularly, a realistic correlation between investment rate, average Q, and cash flow ratio can be reproduced when firms are decreasing returns to scale and are subject to idiosyncratic shocks with low persistence and high variance in an economy that only allows internal financing. When the profitability has low persistence and high variance, the realization of an extreme shock would affect near-term cash flows and hence investment rates when the financial constraints are binding, but it only affects firms' long-term value to a small extent. Moreover, the extent of the decreasing return to scale determines how likely the financial constraints are binding in the stationary distribution. This particular shock structure, together with binding financial constraints, results in a negligible correlation between investment rate and Q, and a positive correlation between investment rate and cash ratio. In the absence of financial frictions, the simulated moments, especially the investment regression coefficients, deviate more from the observed ones.

This conclusion holds for both state-owned firms and private firms. In the data, there are positive correlations between investment rate and cash flow ratio for both state-owned firms and private firms. State-owned firms have a smaller sample mean of Q ratio, a smaller standard deviation of cash ratio, and a lower serial correlation of investment rates. The distinction between the targeted moments leads to the different estimates of model parameters: in the preferred model specification, namely the model with financial constraints, PEs have a more decreasing return-to-scale revenue function, a more persistent and more volatile profitability process, and a smaller adjustment cost.

As opposed to the standard Q theory, the investment regression coefficients are not sensitive to the change in the scale parameter of the adjustment cost when there are financial constraints. In the estimation, the correlation between investment rate and Q is mostly sensitive to the variance of the shock, and the correlation between investment rate and cash ratio is mostly sensitive to the degree of decreasing returns to scale. In the model with financial frictions, capital investment is smoothed by the constraints as it cannot exceed the internal funding of each period, which is a function of the beginning-of-period capital stock. The adjustment cost therefore plays a limited role in determining the investment rate in the model with constraints compared to the model without constraints. This is demonstrated by the low elasticities of simulated moments to the adjustment cost parameter around the parameter estimates for the constrained model.

The model also predicts that firms with small capital stock and median profitability are more likely to be constrained. This also means that firms with median/high average Q and median cash flow ratio are more constrained. Smaller firms are more constrained because the marginal revenue of capital is higher and the available cash flow is lower. When the profitability shock has low persistence and high variance, firms with median profitability would have sufficient incentive to invest but not sufficient revenue to finance the investment.

This paper is related to the literature that discusses investment regressions from a structural perspective. One strand of the literature challenges the interpretation of positive investment-cash flow sensitivity as evidence of financial frictions. The observed correlation between investment rate, average Q, and cash flow ratio may be due to measurement errors in measuring Q or other variables in the regression(Erickson and Whited, 2000; Gomes, 2001). It can also be obtained in models assuming market power and decreasing returns to scale even in the absence of financial constraints(Cooper and Ejarque, 2003). The nature of the fundamental shocks that affect investment rate, firms' long-run growth, and cash flow may also explain the investment regression results in an environment with a perfect capital market (Abel and Eberly, 2011). There is another strand of literature showing that financial frictions can be a contributing factor to the observed cash effect in the investment regression. Cao et al. (2019) shows that the correlation between investment rate, Tobin's Q, and cash flow ratio can be explained by the structure of persistent and temporary shocks, together with financial frictions. Abel and Panageas (2022) shows that even when the Hayashi conditions hold, i.e., the production is constant returns to scale and the adjust cost is quadratic, the presence of financial constraints can create a wedge between marginal Q and average Q. They show analytically that the coefficient on cash flow reflects both the impact of the financial constraints and the impact of the expectation of future profitability, and the coefficient on average Q understates the impact of the profitability.

This paper contributes to understanding the typical investment regression results for Chinese firms. I find that the presence of financial frictions brings the standard capital adjustment model closer to the data of Chinese firms, even when assuming decreasing returns to scale of capital in the revenue function. This exercise does not rule out the possibility of other explanations for the investment regression results such as measurement error in the regression variables, nor does it directly indicate the presence of financial frictions in the Chinese economy. However, it shows that even if market power can generate spurious cash effect in the absence of financial frictions as argued by Cooper and Ejarque (2003), the presence of financial frictions helps to match the moments for the Chinese listed firms in a standard capital adjustment model. This conclusion holds for both state-owned firms and private firms in the sample, which are conventionally considered to have different financial conditions.

The remainder of the paper is organized as follows. Section 2 presents the data and the data moments, including the investment regression results. Section 3 presents the model setup. Section 4 discusses the structural estimation results. Section 5 concludes.

2 Investment Regression

2.1 Data

The sample is Chinese publicly listed firms from 2008 to 2019. The accounting data from 1990 to 2019 are collected and published by CSMAR database. The information that I use to construct the variables in the analysis includes fixed assets (original value), accumulated depreciation, current year depreciation, shareholders' equity, total liabilities, total assets, cash stock, receivables, prepayments, trading financial assets and financial assets available for sale, held-to-maturity investment, derivative financial assets, notes receivables, investment properties from firms' end-of-the-year balance sheet; operating profit, operating tax, financing fees from income statement; current amortization of intangible assets, amortization of long-term deferred expenses from cash flow statement; end-of-the-year firm market value; the classification of the nature of actual controllers and stakeholders; the classification of sector and other firm identifiers[1]. I also collect the price index of capital goods from the Chinese Statistical Bureau.

[1]The indexes of the tables are FS_Combas, FS_Comins, FS_Comscfi, FI_T10, EN_EquityNatureAll, TRD_Co.

The items above are merged by stock code and year across tables. I keep the observations of firms that were actively traded from 2008 to 2019. I also exclude firms with observations of less than three consecutive years. The sample is an unbalanced panel with 18,291 firm-year observations (2,129 firms), out of which 6611 observations (647 firms) are state-owned firms and 11,680 observations (1,584 firms) are private-owned firms.

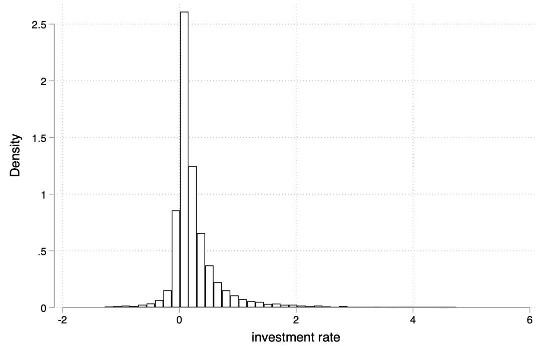
I explain the construction of the variables below. Table 2 describes the variables for the overall sample and the subsamples of SOE and PE.

Capital Stock - The stock value of capital is recovered by the perpetual inventory method using all the information from 1990 to 2019. I obtain the gross investment every year by the change in the reported gross value of fixed assets. The nominal amount of gross investment every year is deflated to the base-year price, set as the price in 1990, by the capital goods price index. To infer the initial capital stock k_0, I assume a linear depreciation process and a depreciation period of 40 years, and then use the ratio of the accumulated deprecation over the original value to estimate the average age of capital assets and thus the "average" purchasing year of the assets. I also assume the purchasing year of the assets is no earlier than 1991 (or the price change before 1991 is negligible), and infer k_0 by deflating the reported book value of fixed assets in the purchasing year. I use the sample mean of the in-use depreciation rate during the sample period, which is 0.0990. Yan (2012) finds a median depreciation rate of 9.5% in a sample of above-scale Chinese manufacturing firms during 2005-2007, and she uses 10% as the depreciation rate in the construction of capital stock. Brandt et al. (2012) uses a depreciation rate of 9% in the construction of capital stock with a sample of above-scale manufacturing firms during 1998-2007. The capital stock is imputed by the capital accumulation process $k_{t+1} = k_t(1 - \delta) + i_t$. State-owned firms are on average larger in capital size than private firms in the sample.

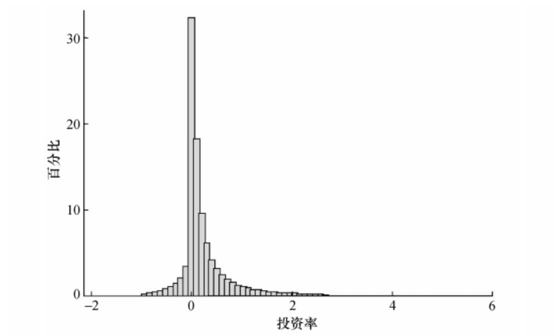
Investment Rate - The investment rate of year t is $\frac{i_t}{k_t}$. I exclude the observations in the bottom and top percentile. Figure 1 and Table 1 compares the distribution and several moments of the investment rates with the ones in Yan (2012), which uses a sample of above-scale manufacturing firms during 2005-2007. From Figure 1, the distributions in these two samples are similar both in shape and range. There are more observations around zero in Yan (2012) as their sample includes small firms, while the sample I use is large firms with multiple plants. The average investment rate is 0.2823 during the sample period, which is much higher than the average investment rate found in Yan (2012) from 2005 to 2007. The higher average investment rate may be due to the sample's selection of large, publicly traded companies and/or the fact that the economy was in a different state during the 2008-2019 period. The average investment rate of state-owned firms is significantly lower than that of private firms (20.63% compared to 32.89%).

I also adjust the raw investment rate by removing the sector-year fixed effects[2]. As shown in Table 1, most of the moments remain similar to the ones in the raw data, but the standard

[2] I regress the investment rates on sector-year fixed effects and add the constant (which is the sample mean) to the residuals from the regression.



(a) Investment Rates of Listed Firms, 2008-2019



(b) Yan(2012)

Figure 1: Investment Rate of Chinese Firms

Note: Panel(a) shows the distribution of investment rates of the CSMAR sample. Panel(b) is taken from Yan(2012) Figure 1. Yan(2012) uses a balanced panel of above-scale Chinese manufacturing firms from 2005 to 2007.

deviation is smaller since the variation due to sector-year heterogeneity is cleaned out. The serial correlation of investment rate is around 0.0551 in the raw data and is 0.0373 after the sector-year adjustment.

Table 1: Investment Rate Moments in Different Samples

	Overall Capital								
	mean	s.d.	auto corr.	> 0.2	< -0.2	$(0.1, 0.2)$	$(-0.2, -0.1)$	$(-0.01, 0.01)$	< 0
raw	0.2823	0.5080	0.0551	0.3956	0.0276	0.1845	0.0187	0.0484	0.1161
adj. sector-year	0.2823	0.4973	0.0373	0.4341	0.0337	0.2083	0.0363	0.0307	0.1672
Yan (2012)	0.1978	-	0.0173	0.3502	0.0408	0.1446	0.0226	0.1451	0.1678

Note: This table shows the sample mean, standard deviation, serial correlation, and the shares of firm-year observations with investment rate in the corresponding range. The first row shows the moments calculated using the raw data, and the second row shows the moments adjusted for sector-year fixed effects. Yan(2012) uses a balanced panel of Chinese manufacturing firms from 2005 to 2007. Their sample covers unlisted and smaller firms.

Average Q - I follow Hall (2001) and Crouzet and Eberly (2023) to construct the average Q ratio. The firm's value is approximated by the market value of all net claims on the firm, which is the sum of the market value of debt and equity minus the market value of financial assets. In my calculation, the market value of debt is approximated by its book value. The financial assets include cash, marketable securities/bonds/derivatives/properties, and operating financial assets such as receivables and prepayments. The average Q ratio is the ratio between the value of the firm and the value of the non-financial assets. I find the sample mean of the average Q ratio to be 2.8393. The mean average Q of state-owned firms is 2.55, which is significantly lower than private firms' 3.01. Crouzet and Eberly (2023) reports a range of 1.1 to 2.5 of average Q for physical capital for the nonfinancial corporate business sector in the U.S. and a range of 1.7 to 2.2 for the Compustat nonfinancial sample. Cooper and Ejarque (2003) targeted at a mean average Q of 3 as in Gilchrist and Himmelberg (1995).

Cash Flow Ratio - Since I assume time-to-build for capital adjustment in the model in section 3, firms' revenue π_t is a function of k_{t-1}. The cash flow ratio is therefore $\frac{\pi_t}{k_{t-1}}$. The revenue is the cash flow net of labor cost and before investment expenditure, which is approximated by earnings before interest, tax, depreciation, and amortization (EBITDA) and obtained by adding back the sum of operating tax, financing cost, depreciation, and amortization to operating profit. I deflate the nominal value with a capital goods price index so that both the numerator and denominator are in terms of capital. The sample mean of cash flow ratio is 0.57; the average cash flow ratio of private firms is significantly higher than that of state-owned firms.

Table 2: Descriptive Statistics

A: Overall

	mean	sd	p25	p50	p75	N
log(capital stock)	19.33	1.55	18.29	19.20	20.21	17242
investment rate	0.28	0.51	0.04	0.14	0.34	15689
average q	2.84	2.25	1.44	2.10	3.35	17430
cash	0.57	0.71	0.20	0.37	0.69	15658

B: Private Firms vs. State-owned Firms

	SOE			PE			
	mean	sd	N	mean	sd	N	Diff in Mean
log(capital stock)	20.10	1.63	6151	18.90	1.32	11091	1.202***
							(52.66)
investment rate	0.21	0.43	5962	0.33	0.55	9727	-0.123***
							(-14.77)
average q	2.55	2.19	6410	3.01	2.27	11020	-0.457***
							(-12.98)
cash flow ratio	0.45	0.67	5992	0.63	0.72	9666	-0.181***
							(-15.68)

*Note: The statistics describe the constructed variables for all the observations and for the sub-samples of state-owned firms and private firms. T-statistic in parentheses. * p<0.05, ** p<0.01, *** p<0.001.*

2.2 Investment-Cash Flow Sensitivity

Table 3 and Table 4 present the coefficient estimates of the investment regression as in equation (1). i_t, q_t, and cf_t are respectively investment rate, average Q, and cash flow ratio at year t. The different columns are regression results controlling for different fixed effects.

Table 3 shows that the correlation between investment rate and Q ratio is close to zero while the correlation between investment rate and cash flow ratio is positive and significant. The investment-cash flow sensitivity is around 0.32 when the regression controls for firm fixed effects and thus exploits within-firm variation, as shown in columns (1) and (3). It is around 0.199 when the regression exploits within sector-year variation as in column (2). Cooper and Ejarque (2003) summarizes the investment regression results in their Table 1, and the investment-cash flow sensitivity ranges from 0.14 to 0.46. The structural estimation in section 4 uses the regression coefficients in column (3): the coefficient estimate on average Q is not significantly different from zero, and the coefficient estimate on cash flow ratio is significantly positive and is around 0.3191.

The regressions for the subsamples of the state-owned firms and the private firms have similar results and are shown in Table 4. Moreover, the point estimates of the investment-cash flow sensitivity have a larger magnitude for private firms compared to state-owned firms in all the specifications, though the differences are not very significant.

$$i_t = c + b_q \cdot q_t + b_{cf} \cdot cf_t \tag{1}$$

Table 3: Investment Regression

	Investment Rate		
	(1)	(2)	(3)
average Q	0.0014	-0.0098**	0.0017
	(0.004)	(0.003)	(0.004)
cash ratio	0.3197***	0.1991***	0.3191***
	(0.022)	(0.013)	(0.022)
Firm FE	Yes	No	Yes
Year FE	Yes	No	No
Sector-year FE	No	Yes	Yes
Observations	14008	14057	14005
Adjusted R^2	0.144	0.096	0.147

*Standard errors in parentheses, double clustered at sector-year level and firm level. * p<0.05, ** p<0.01, *** p<0.001.*

Table 4: Subsample Investment Regression

	Investment Rate					
	SOE			PE		
	(1)	(2)	(3)	(4)	(5)	(6)
average Q	0.0034	-0.0058	0.0040	0.0021	-0.0107**	0.0025
	(0.007)	(0.005)	(0.007)	(0.005)	(0.003)	(0.005)
cash ratio	0.3099***	0.1697***	0.3109***	0.3220***	0.2134***	0.3200***
	(0.031)	(0.019)	(0.031)	(0.030)	(0.018)	(0.030)
Firm FE	Yes	No	Yes	Yes	No	Yes
Year FE	Yes	No	No	Yes	No	No
Sector-year FE	No	Yes	Yes	No	Yes	Yes
Observations	5252	5242	5209	8708	8764	8698
Adjusted R^2	0.101	0.057	0.094	0.140	0.099	0.148

*Standard errors in parentheses, double clustered at sector-year level and firm level. * p<0.05, ** p<0.01, *** p<0.001.*

3 Model

Firms' investment decisions are characterized by the following capital adjustment problem. It is similar to the neoclassical setting in Hayashi (1982), which lays the theoretical foundation of Q theory and the reduced-form investment regression. Some papers, such as Cooper and Ejarque (2003) and Crouzet and Eberly (2023), study the variants of this model to understand the investment-Q regression results. Eberly et al. (2008) shows that this model provides a good characterization of firms' capital investment behavior.

Firms are subject to an idiosyncratic shock z and determine their capital stock K with time to build. The value function is equation (2). The shock $log(z)$ follows an AR(1) process. $C(K, K') = \frac{\gamma}{2}\frac{(K'-K(1-\delta))^2}{K}$ is the quadradic adjustment cost. As in Cooper and Ejarque (2003), the revenue function can be decreasing returns to scale, i.e., $\pi(K, z) = zK^{\alpha}$, $\alpha \leq 1$. The capital price is normalized to one.

$$V(K, z) = \underset{K' \geq 0}{max} \quad \pi(K, z) - (K' - (1-\delta)K) - C(K, K') + \beta \mathbb{E}_{z'|z} V(K', z') \tag{2}$$

Financial frictions are in the form of the starkest financial constraint, which forces firms to use only internal funds for capital investment. It is represented by a resource constraint as in inequality (3).

$$K' - (1-\delta)K \leq \pi(K, z) \tag{3}$$

The model parameters include $\beta, \delta, \alpha, \rho_z, \sigma_z, \gamma$. Given the predefined parameters β and δ, I estimate $\Theta = [\alpha, \rho_z, \sigma_z, \gamma]$ by the simulated method of moments. In the first model specification, firms solve equation (2) subject to the financial constraint (3). This means that capital investment can only be financed by firms' internal funding. I denote this economy as the constrained economy. In the second specification, firms solve equation (2) without any financial constraints. This is called the unconstrained economy. The details of the estimation procedure are explained in section 4.1.

4 Structural Estimation

4.1 Estimation Procedure

The SMM estimator minimizes the distance between the data moments M and the simulated moments $\tilde{M}(\Theta)$ as in equation (4). W is the weighting matrix. For a given set of the model parameters $[\beta, \delta, \alpha, \rho_z, \sigma_z, \gamma]$, I solve the capital adjustment model and simulate a stationary distribution of 3000 firms for 100 periods. I compute the simulated moments using the simulated data. $\tilde{M}(\Theta)$ is thus a function of Θ. Table 5 summarizes the model parameters and targeted moments in the estimation.

$$\hat{\Theta}_{smm} = \underset{\Theta}{argmin}(M - \tilde{M}(\Theta))'W(M - \tilde{M}(\Theta)) \tag{4}$$

Data Moments - There are five targeted data moments in the structural estimation. The coefficient estimates from the investment regression are the main observational facts discussed in this paper. The coefficient estimate on average Q ratio is zero, and the coefficient on cash flow ratio is 0.3191 for the overall sample, 0.3109 for the state-owned firms, and 0.3200 for the private firms.

In addition, I follow Cooper and Ejarque (2003) and use three other targeted moments. First, the sample mean of average Q is informative for the curvature of the revenue function. Second, the standard deviation of the cash flow ratio is directly associated with the standard deviation of the profitability shock. I first regress the constructed cash flow ratio on firm and sector-year fixed effects, obtain the residuals, and compute the standard deviation of the regression residuals. This is to filter out the variations that are not due to idiosyncratic shock, and it leads to a lower standard deviation. The standard deviation is 0.71 for the raw cash flow ratio in the full sample, and it is 0.46 after the adjustment. Lastly, the serial correlation of investment rate is informative for the adjustment cost scale and also

Table 5: Parameters and Moments in Structural Estimation

	Description	Value
A. Predefined Parameters		
δ	in-use depreciation rate	0.0990
β	discount factor	0.9524
B. Estimated Parameters		
α	curvature of revenue function	
ρ_z	idiosync. profitability process: persistence	
σ_z	idiosync. profitability process: stand. dev.	
γ	quadratic adj. cost	
C. Targeted Moments		
b_q	reg. coef. on Q ratio	
b_{cf}	reg.coef. on cash flow ratio	
$\overline{ave.Q}$	sample mean of average Q	
$std(cf\%)$	standard deviation of cash flow ratio	
$corr(i'\%, i\%)$	serial correlation of investment rate	

the persistence of the profitability shock. Similarly, the raw investment rate is adjusted for the sector-year fixed effects. I then calculate the correlation coefficient between the adjusted investment rate at year t and the one at year $t-1$. The obtained serial correlation is 0.0373, compared to 0.0173 in Yan (2012).

The vector of the moments is denoted as $[b_q, b_{cf}, \overline{ave.Q}, std(cf\%), corr(i'\%, i\%)]$, and the definitions are presented in Table 5 panel C. The values of these data moments are presented in Table 6. In comparison to the set of targeted moments in Cooper and Ejarque (2003), the standard deviation of cash flow ratio is larger and the serial correlation of investment rate is lower in the Chinese Sample. In section 4.2, I show that these moments are sensitive to the corresponding parameters in the simulation.

Predefined Parameters - The depreciation rate δ is fixed at 0.0990, which is the sample mean of the depreciation rates in use and the depreciation rate used to construct the capital stock in the perpetual inventory method. It is also consistent with the literature as discussed in section 2.1. The discount factor β is set to be 0.9524, which corresponds to an interest rate of 5% per year[3]. The remaining model parameters are α, ρ_z, σ_z, and γ, which need to be estimated.

Weighting Matrix - I use both the identity matrix and the inverse of the variance-covariance matrix of the data moments as the weighting matrix in the estimation. The latter is the so-called optimal weighting matrix and improves the efficiency of the estimator. The variance-covariance matrix of the data moments is obtained by block bootstrap clus-

[3]when $\beta(1+r) = 1$.

Table 6: Targeted Data Moments

	b_q	b_{cf}	$\overline{ave.Q}$	$std(cf\%)$	$corr(i'\%, i\%)$
A. Chinese Sample					
Overall	0	0.3191	2.8393	0.4586	0.0373
SOE	0	0.3109	2.5474	0.4188	0.0130
PE	0	0.3200	3.0059	0.4606	0.0296
B. GH95					
	0.03	0.24	3.00	0.25	0.40

Note: Panel A presents the data moments of the sample and the subsamples described in section 2.1. Panel B is taken from CE() Table 1.

tered at the firm level for 500 times. The optimal weighting matrix puts more weight on the moments with lower variance and with lower covariance with other moments, as these moments are more precise and more informative for the identification of the parameters. Table 7 presents the optimal weighting matrix using all the observations of the full sample. I also show the optimal weighting matrices for SOEs and PEs in the appendix Table A3. From the diagonal entries, we see that the weight on b_q is high. This is because of the low variance of b_q, which is also demonstrated by its low standard error displayed in Table 3 column (3). $\overline{ave.Q}$ has a high variance and is also very correlated with b_{cf}, and is therefore given a low weight in the estimation.

Table 7: Optimal Weighting Matrix

	b_q	b_{cf}	$\overline{ave.Q}$	$std(cf\%)$	$corr(i'\%, i\%)$
b_q	59700				
b_{cf}	1880	3250			
$\overline{ave.Q}$	716	-8	891		
$std(cf\%)$	535	1920	-801	8880	
$corr(i'\%, i\%)$	1680	781	-412	730	14000

Note: This table presents the inverse of the variance-covariance matrix of the data moments for the full sample. The variance-covariance matrix of the data moments is obtained by block bootstrap clustered at the firm level for 500 times.

Standard Errors - When W is the optimal weighting matrix, the variance-covariance matrix of $\hat{\Theta}$ is estimated by a sandwich estimator as equation (5). $M_\Theta \equiv [\frac{\partial m(\Theta)}{\partial \theta}]$ is the Jacobian matrix, and each entry shows how sensitive a simulated moment $m(\Theta)$ is to a model parameter θ around the SMM estimates $\hat{\Theta}$. W_{opt} is the inverse of the variance-covariance matrix of the data moments. $\tilde{W}$ is the inverse of the variance-covariance matrix of the simulated moments. Intuitively, the first term measures the error from the estimation of the data moments: the more precise a data moment is and the more sensitive a parameter is to that data moment (which means a larger weight in W_{opt} and a larger partial derivative in $M(\Theta)$), the more precise this parameter estimate will be and the smaller the standard error will be. Similarly, the second term measures the noise from the simulation and is smaller if the parameters are more sensitive to the simulated moments that have smaller variances.

$$(M'_\Theta W_{opt} M_\Theta)^{-1} + (M'_\Theta \tilde{W} M_\Theta)^{-1} \tag{5}$$

As explained above, the optimal weighting matrix W_{opt} is obtained by block bootstrap on the observed data. Similarly, $\tilde{W}$ is obtained by block bootstrap on simulated data with the dimension 10,000 firms $\times$ 500 periods for 100 times. The standard errors are computed as the square root of the diagonal entry of the estimated variance-covariance matrix.

4.2 Estimation Results

4.2.1 Constrained Economy versus Unconstrained Economy

Table 8 Panel A presents the SMM estimates of the parameters using the optimal weighting matrix and targeting at the moments calculated with the full sample. Table 8 Panel B compares the simulated moments and the targeted data moments and presents the value of the distance function in equation (4). The last row presents the result of a counterfactual exercise and displays the simulated moments in the unconstrained model given the estimates of the constrained economy. The estimation results using the identity weighting matrix are presented in Table A1 and Table A2 in the Appendix.

The model with financial constraints matches the data moments better as the value of the distance function (4) is smaller than the one of the model without constraints. This is also true when the weighting matrix is an identity matrix. Moreover, the estimates from the unconstrained model have bigger standard errors and are less precise in general. Also, the parameter estimates for the constrained economy are similar regardless of whether the weighting matrix is the optimal matrix or the identity matrix, while the estimates for the unconstrained economy vary considerably depending on the weighting matrix. I will discuss the parameter identification in the next part.

The revenue function is decreasing returns to scale ($\hat{\alpha} < 1$). Cooper and Ejarque (2003) stresses the importance of market power in explaining the positive investment-cash flow sensitivity, which can be present in a model without financial frictions. The estimated persistence of the idiosyncratic shock is low ($\hat{\rho_z} = 0.1712$) in the model with financial frictions. Non-persistent shocks, combined with financial frictions, can generate a low correlation between investment rate and average Q, and a positive investment-cash flow sensitivity. Intuitively, a shock with low persistence has a small effect on firm value but can affect near-term cash flows and hence investment rates when there are binding financial constraints. Cao et al. (2019) has a similar conclusion in a model with constant returns to scale and financial constraints.

The last row of Table 7 Panel B shows the simulated moments from an unconstrained model given the constrained model parameter estimates. The moments obtained deviate more from the data moments, by a distance of 6000 compared to 110 for the simulation of the constrained model. In this simulated data, the serial correlation of investment rates is negative. When capital investments are bounded by firms' revenues/cash flows in the constrained economy, investment rates are smoothed by the binding constraints and are more positively correlated across periods. Without financial frictions, firms' investments are not bounded by their internal funding and thus less likely to be positively auto-correlated. Interestingly, in the absence of financial frictions, b_q can be positive and big even with an α smaller than one and a small ρ_z. The coefficient on cash ratio appears to be negative, conditional on average Q.

For the unconstrained model, the persistence parameter ρ_z is estimated to be 0.2193, and the adjustment cost parameter γ is 2.6197. These two parameters, especially $\hat{\gamma}$, are larger compared to the ones for the constrained model. First, a higher persistence can generate a higher $corr(i'\%, i\%)$. Second, investments are also smoothed by the larger quadratic adjustment cost so that $corr(i'\%, i\%)$ can be higher. Moreover, the large adjustment cost can suppress the investment response to shocks, which tones down the regression coefficients b_q and b_{cf}. However, the difference between the simulated moments and the data moments is still large. b_q is still much larger than zero, and the simulated b_{cf} is negative. $corr(i'\%, i\%)$ is too high compared to the one in the data. $\overline{ave.\,Q}$ is also higher than the observed one.

In the appendix, Table A1 shows that $\hat{\rho}_z$ for the unconstrained model is 0.3791 and $\hat{\gamma}$ is 0.1899 if the weighting matrix is an identity matrix. The corresponding b_{cf} in the simulated data is 0.3113, which is close to the observed data moment. However, the simulated b_q is 0.1913 and is way higher than the one in the data. The wedge between marginal Q and average Q in this case results in positive and large b_q and b_{cf}. The difference between the two sets of parameter estimates in Table 8 and Table A1 is simply due to the different weights on the targeted moments, especially the one on b_q.

Parameter Identification - Table 9 shows the elasticity matrices of the simulated moments to the parameters in the two model specifications. Each entry is the elasticity of a simulated moment with respect to a model parameter in the neighborhood of the parameter estimates. These elasticities also indicate which parameters are identified by which moments. The more sensitive a moment is to a parameter, the more informative the moment is in the identification of the parameter. In the Appendix Figure A1 to Figure A8, I also show how the five targeted moments move with α, ρ_z, σ_z, and γ, respectively, in the neighborhood of their estimated value.

In the constrained economy, $\overline{ave.\,Q}$ is sensitive to α, and $std(cf\%)$ is sensitive to σ_z. As financial frictions smooth capital investment as quadratic adjustment cost, $corr(i'\%, i\%)$ is

Table 8: Parameter Estimates and Targeted Moments

A. Model Parameter Estimates

	α	ρ_z	σ_z	γ
internal funding	0.7169	0.1712	2.0056	0.1689
	[0.0090]	[0.0140]	[0.0415]	[0.0266]
unconstrained	0.6531	0.2193	1.6858	2.6197
	[0.0076]	[0.0712]	[0.0900]	[0.2587]

B. Simulated and Data Moments

	b_q	b_{cf}	$\overline{ave.Q}$	$std(cf\%)$	$corr(i'\%, i\%)$	Distance
internal funding	0.0386	0.2957	2.8293	0.5096	0.0451	110.7406
unconstrained	0.0976	-0.0805	3.2820	0.5075	0.1245	1151.5681
Data	0.0000	0.3191	2.8393	0.4586	0.0373	-
unconstrained-cnf	0.3139	-0.1140	2.3839	0.4653	-0.0555	6000.8674

Note: The estimates in Panel A are obtained using the optimal weighting matrix in the simulated method of moments. The standard errors are in the parentheses. The first row of Panel A presents the estimates of the parameters for the model with financial constraints, and the second row presents the estimates of the parameters for the model without financial constraints. Panel B presents the targeted moments and the value of the objective function in equation (4) with W being the optimal weighting matrix. The first two rows of Panel B are the simulated moments given the obtained estimates in the corresponding models. The third row shows the targeted data moments. The last row displays the simulated moments in the unconstrained model given the estimates of the constrained economy.

more sensitive to ρ_z than to γ. The serial correlation is also sensitive to α and is increasing in α. The less decreasing to scale of the revenue function, the less the market power, and the more likely financial constraints are binding. This means capital investments are more likely to be smoothed and are more positively auto-correlated. Similarly, as a higher α leads to more binding financial constraints, the investment-cash flow sensitivity b_{cf} is informative in identifying α and is increasing in α, as shown in Figure A1. The investment regression coefficient b_q is informative in identifying σ_z and is decreasing in σ_z, as shown in Figure A3. The intuition is that as the profitability shocks become more dispersed, the realization of more extreme shocks has a limited effect on firm value but a large effect on investment rate, resulting in a lower correlation between investment rates and average Q.

In the unconstrained economy, however, investment is not bounded, and the investment regression coefficients b_q and b_{cf} are sensitive to all the parameters, especially to the adjustment cost parameter γ. Also, $corr(i'\%, i\%)$ is more elastic to γ without the smoothing effect of financial frictions.

Table 9: Elasticity Matrix

A. Internal Funding				
	Model Parameters			
Targeted Moments	α	ρ_z	σ_z	γ
b_q	0.66	-0.29	-1.80	-0.11
b_{cf}	2.34	0.70	0.85	-0.45
$\overline{ave. Q}$	-1.60	0.14	0.89	0.03
$std(cf\%)$	-0.95	0.04	1.43	0.04
$corr(i'\%, i\%)$	2.68	1.35	-0.29	0.74
B. Unconstrained				
	Model Parameters			
Targeted Moments	α	ρ_z	σ_z	γ
b_q	6.31	-2.54	7.05	11.81
b_{cf}	8.63	-3.87	8.41	16.13
$\overline{ave. Q}$	-2.08	-0.09	-0.53	0.25
$std(cf\%)$	-1.21	0.04	0.72	0.18
$corr(i'\%, i\%)$	-1.41	5.52	8.97	-13.33

Note: This Table presents the elasticity matrices of the simulated moments to the parameters in the models with and without financial constraints. The (i, j) *entry of each matrix is the elasticity around the point estimates approximated by* $e_{i,j} \approx \frac{\Delta log(m_i)}{\Delta log(\theta_j)}$*, where* m_i *is a targeted moment and* θ_j *is a parameter. For example, the first entry of Panel A means that around* $\hat{\alpha} = 0.7169$ *in the constrained economy, with a* 1% *change in* α, b_q *changes by* 0.66%.

Binding Constraints - The financial constraints in the constrained model are occasionally binding. Given the parameter estimates in the constrained economy, Figure 2 plots the resource (green line), the capital policy k_{t+1} in the constrained economy (blue dash line), and the capital policy k_{t+1} if there are no financial constraints (orange dash line), as a function of k_t conditional on low, median and high profitability. k_{t+1} cannot exceed a firm's resource $\pi_t + (1-\delta)k_t$ in the internal funding case.

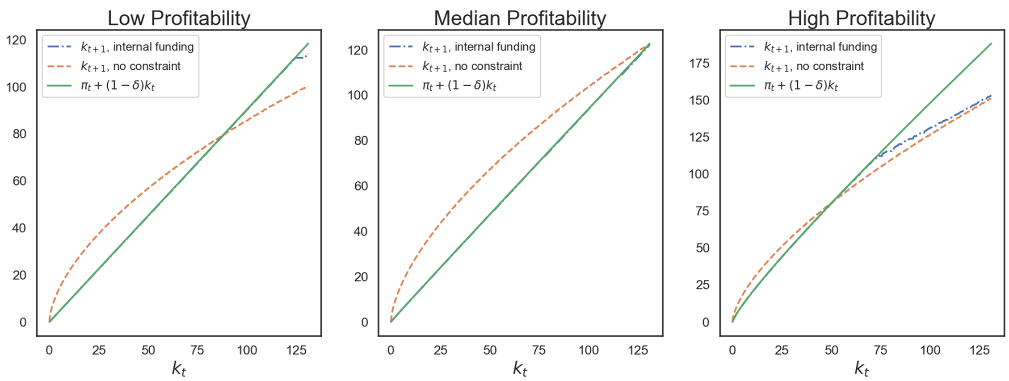


Figure 2: Policy Functions

Note: The policy functions are solved given the parameter estimates from the model with financial constraints. The profitability process is discretized into seven states using the Tauchen's method. The low, median, and high profitability correspond to the 2nd, the 4th, and the 6th profitability states from low to high values, respectively.

The constraints are binding when the unconstrained investment would have exceeded the internal funding if there were no financial constraints. In Figure 2, this means when the orange dash line is above the blue dash line. The constraints are more likely to bind when the capital stock is low and the profitability is median or low. The marginal revenue of capital is decreasing in capital stock and increasing in profitability. And the available internal funding is increasing in capital stock and increasing in profitability. Therefore, the profitability shock affects the capital investment both through affecting the current available resources and through affecting the future marginal revenue of capital. With a low persistent profitability process, it is when the profitability is at the median that firms are most likely to be constrained because they have sufficient incentive to invest but not sufficient resources.

Figure 2 also shows that the constrained investment can exceed the unconstrained investment when capital stock is relatively high. Firms engage in precautionary saving when financial constraints may bind in the future.

Figure 3 presents the fraction of constrained firms as a function of profitability, capital size, average Q, and cash flow ratio. I first simulate the constrained economy of 10000 firms for 550 periods. I drop the first 500 periods and obtain a stationary distribution with 10000 firms and 50 periods. The variable $log(profitability)$ has only seven values through the discretization. The variables $capital$, $averageQ$, and $log(cashratio)$ are grouped into bins of deciles. The constraints are binding when the unconstrained capital policy would have exceeded the resource, and the dummy variable that indicates the binding states is obtained by solving both the constrained and the unconstrained models under the same set of parameters. Each point in Figure 3 shows the fraction of constrained firms in each bin. As indicated by the policy functions in Figure 2, firms are more likely to be constrained when the profitability is relatively low and when the capital size is small. The fraction of constrained firms first increases and then decreases in profitability, average Q, and cash flow ratio. It decreases in capital size.

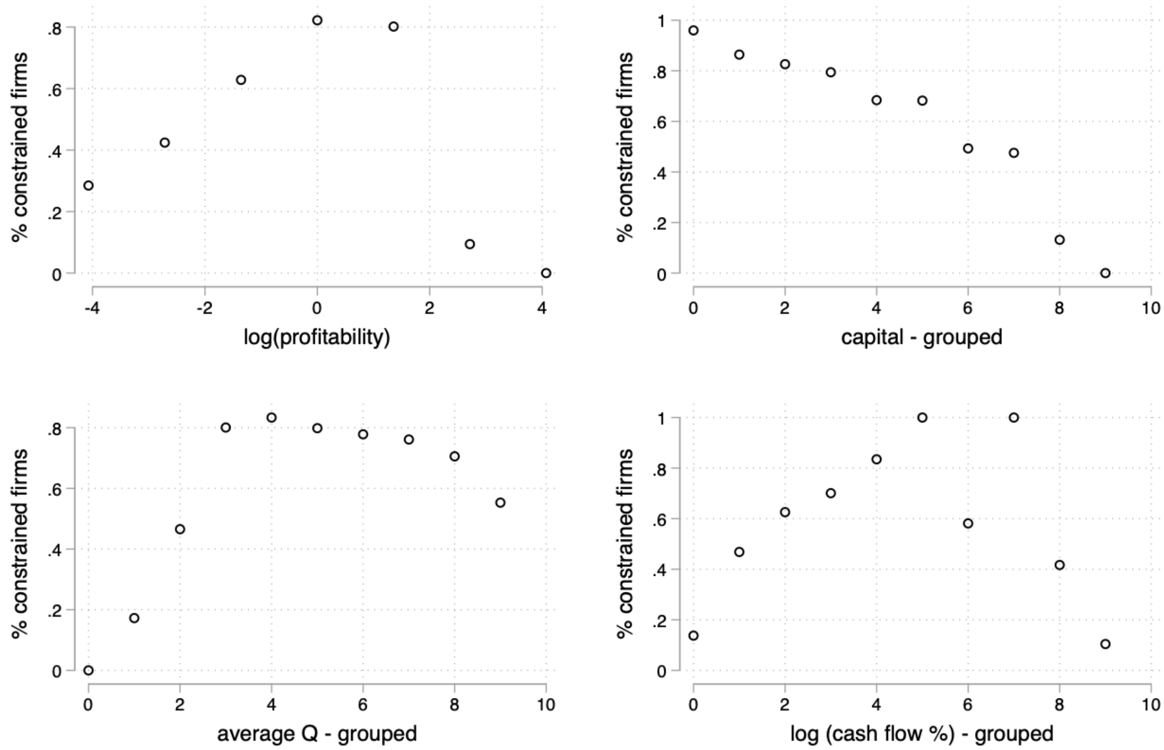


Figure 3: Binding States in the Stationary Distribution

Note: Each point means the fraction of constrained firms within each bin in the stationary distribution. The stationary distribution is obtained by simulating the model with financial constraints given the parameter estimates.

4.2.2 SOE versus PE

Table 10 presents the parameter estimates targeted at the data moments of the subsamples of state-owned firms(SOE) and private firms(PE). The weighting matrix is computed by bootstrapping on the corresponding subsample as described in section 4.1, and is presented in Table A3. The estimation results obtained using the identity matrix as the weighting matrix are presented in Table A1 and Table A2. The data moments are better matched by the model with financial frictions for both SOE and PE.

In the model with financial constraints, which is favored by the estimation results, the parameter estimates for the two subsamples are different. Firstly, the estimate of α for PE is smaller than that for SOE, which is consistent with the higher $\overline{ave.Q}$ of the private firms. Secondly, the estimates of ρ_z and σ_z for PE are both larger than those for SOE. This is consistent with the higher $corr(i'\%, i\%)$ and the higher $std(cf\%)$ for private firms. Meanwhile, the estimate of γ for PE is smaller than the one for SOE. This is against the lower $corr(i'\%, i\%)$ of PE. However, as discussed in section 4.2.1, when there are financial constraints, $corr(i'\%, i\%)$ is more sensitive to ρ_z and α than to γ.

5 Conclusion

This paper studies the investment-Q regression using a sample of Chinese publicly listed firms. I first show that similar to the previous studies, for both the full sample and the subsamples of state-owned firms and private firms, the investment-Q regression generates a positive and significant coefficient estimate on cash flow ratio and an insignificant coefficient estimate on Q ratio. To explain the investment regression results, I estimate a capital adjustment model with and without financial constraints using the simulated method of moments, and compare the estimation results of the two specifications. The model is estimated by targeting at the investment regression coefficients and some other informative moments for the full sample and the two subsamples. The estimation results suggest that the observed moments, including the positive investment-cash low sensitivity, are better explained by the model with financial constraints. Also, the revenue function is decreasing returns to scale, and the idiosyncratic profitability shock has low persistence and high variance. The exploration of the relationship between the parameters and the moments shows that financial frictions, market power, and shock structure jointly generate the realistic investment regression results. The comparison of the estimation results between SOE and PE shows that the model with financial constraints matches better the data moments of both subsamples, though the point estimates of the model parameters are different.

In this paper, I assume that state-owned firms and private firms are subject to the same financial constraints, which restrict firms' capital investments to be financed only through their internal funds. It is an interesting question to ask whether SOE and PE face heterogeneous financial constraints, and it can be answered by studying a model that allows borrowing and allows the degree of financial frictions to be different between SOE and PE in the future.

Table 10: Parameter Estimates and Targeted Moments for Subsamples

A. Model Parameter Estimates

	SOE			
	α	ρ_z	σ_z	γ
internal funding	0.7581	0.1671	1.9467	0.2233
	[0.0124]	[0.0213]	[0.0706]	[0.0556]
unconstrained	0.6720	0.2190	1.6605	2.6304
	[0.0080]	[0.0046]	[0.0695]	[0.6430]
	PE			
	α	ρ_z	σ_z	γ
internal funding	0.6883	0.1905	1.9839	0.1642
	[0.0066]	[0.0177]	[0.0518]	[0.0236]
unconstrained	0.6486	0.2219	1.6979	2.6167
	[0.0063]	[0.0230]	[0.0490]	[0.0098]

B. Simulated and Data Moments

	SOE					
	b_q	b_{cf}	$\overline{ave.\,Q}$	$std(cf\%)$	$corr(i'\%, i\%)$	Distance
internal funding	0.0403	0.2911	2.5519	0.4693	0.0587	62.3991
unconstrained	0.1022	-0.0849	3.1290	0.4861	0.1314	551.2923
Data	0.0000	0.3109	2.5474	0.4188	0.0130	-
	PE					
	b_q	b_{cf}	$\overline{ave.\,Q}$	$std(cf\%)$	$corr(i'\%, i\%)$	Distance
internal funding	0.0380	0.2930	3.0322	0.5235	0.0474	84.2043
unconstrained	0.0952	-0.0779	3.3195	0.5150	0.1293	675.9744
Data	0.0000	0.3200	3.0059	0.4606	0.0296	-

Note: This table presents the parameter estimates targeted at the data moments of the subsamples of state-owned firms(SOE) and private firms(PE). The estimates in Panel A are obtained using the optimal weighting matrices. The standard errors are in parentheses. Panel B presents the simulated moments and the targeted data moments. The last column shows the value of the objective function in equation (4) with W being the corresponding optimal weighting matrix.

References

Andrew B. Abel and Janice C. Eberly. How Q and Cash Flow Affect Investment without Frictions: An Analytic Explanation. *The Review of Economic Studies*, 78(4):1179–1200, October 2011. ISSN 0034-6527. doi: 10.1093/restud/rdr006.

Andrew B Abel and Stavros Panageas. An Analytic Framework for Interpreting Investment Regressions in the Presence of Financial Constraints. *The Review of Financial Studies*, 35 (9):4055–4104, September 2022. ISSN 0893-9454. doi: 10.1093/rfs/hhab130.

Aydoğan Alti. How Sensitive Is Investment to Cash Flow When Financing Is Frictionless? *The Journal of Finance*, 58(2):707–722, 2003. ISSN 1540-6261. doi: 10.1111/1540-6261.00542.

Loren Brandt, Johannes Van Biesebroeck, and Yifan Zhang. Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics*, 97(2):339–351, March 2012. ISSN 03043878. doi: 10.1016/j.jdeveco.2011.02.002.

Dan Cao, Guido Lorenzoni, and Karl Walentin. Financial frictions, investment, and Tobin's q. *Journal of Monetary Economics*, 103:105–122, May 2019. ISSN 0304-3932. doi: 10.1016/j.jmoneco.2018.08.002.

Russell Cooper and João Ejarque. Financial frictions and investment: Requiem in Q. *Review of Economic Dynamics*, page 19, 2003.

Nicolas Crouzet and Janice Eberly. Rents and Intangible Capital: A Q+ Framework. *The Journal of Finance*, page jofi.13231, May 2023. ISSN 0022-1082, 1540-6261. doi: 10.1111/jofi.13231.

Janice Eberly, Sergio Rebelo, and Nicolas Vincent. Investment and Value: A Neoclassical Benchmark, March 2008.

Timothy Erickson and Toni M. Whited. Measurement Error and the Relationship between Investment and q. *Journal of Political Economy*, 108(5):1027–1057, October 2000. ISSN 0022-3808. doi: 10.1086/317670.

Simon Gilchrist and Charles P. Himmelberg. Evidence on the role of cash flow for investment. *Journal of Monetary Economics*, 36(3):541–572, December 1995. ISSN 0304-3932. doi: 10.1016/0304-3932(95)01223-0.

Joao F. Gomes. Financing Investment. *American Economic Review*, 91(5):1263–1285, December 2001. ISSN 0002-8282. doi: 10.1257/aer.91.5.1263.

Robert E. Hall. The Stock Market and Capital Accumulation. *American Economic Review*, 91(5):1185–1202, December 2001. ISSN 0002-8282. doi: 10.1257/aer.91.5.1185.

Fumio Hayashi. Tobin's Marginal q and Average q: A Neoclassical Interpretation. *Econometrica*, 50(1):213–224, 1982. ISSN 0012-9682. doi: 10.2307/1912538.

Ping Yan. An Investigation into Capital Misallocation. *China Economic Quarterly*, 11(2): 489–520, 2012. ISSN 2095-1086.

Appendix

Table A1: Parameter Estimates

	Parameter Estimates			
	α	ρ_z	σ_z	γ
A. Overall				
internal funding	0.7041	0.1906	1.8654	0.1455
unconstrained	0.7079	0.3791	1.9296	0.1899
B. SOE				
internal funding	0.7391	0.1669	1.8146	0.1535
unconstrained	0.7429	0.3627	1.8937	0.1795
C. PE				
internal funding	0.6785	0.2060	1.8243	0.1363
unconstrained	0.6511	0.2910	1.5119	0.1181

Note: The parameter estimates are obtained using the identity matrix as the weighting matrix in the simulated method of moments. Panel A presents the estimates targeted at the data moments of the full sample. Panel B and panel C present the estimates targeted at the data moments of the subsamples of SOEs and PEs.

Table A2: Simulated and Data Moments

	Targeted Moments					Distance
	b_q	b_{cf}	$\overline{ave.Q}$	$std(cf\%)$	$corr(i'\%, i\%)$	
A. Overall						
internal funding	0.0468	0.3206	2.8391	0.4734	0.0423	0.0024
unconstrained	0.1913	0.3113	2.8582	0.4502	0.1024	0.0413
Data	0.0000	0.3191	2.8393	0.4586	0.0373	-
B. SOE						
internal funding	0.0533	0.3093	2.5478	0.4356	0.0416	0.0039
unconstrained	0.2275	0.3175	2.5694	0.4195	0.0961	0.0592
Data	0.0000	0.3109	2.5474	0.4188	0.0130	-
C. PE						
internal funding	0.0514	0.3217	3.0041	0.4771	0.0361	0.0030
unconstrained	0.2182	0.3025	3.0302	0.3827	-0.0211	0.0571
Data	0.0000	0.3200	3.0059	0.4606	0.0296	-

Note: The simulated moments are computed given the parameters in Table A1. The distance is the value of the objective function in equation (4) with W being the identity matrix.

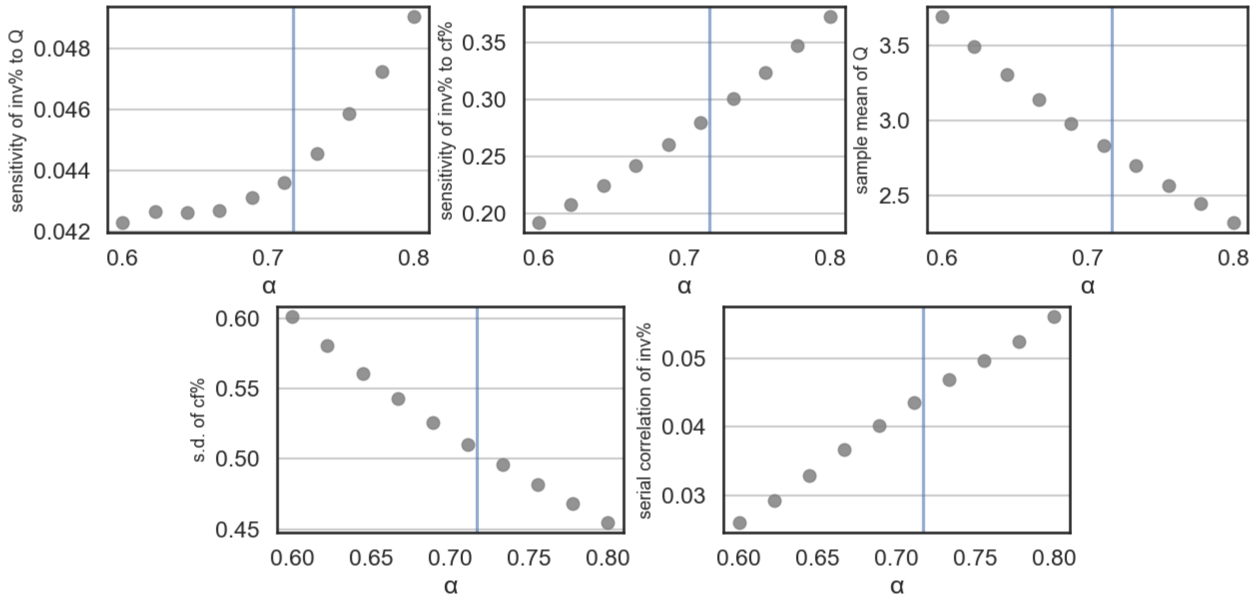


Figure A1: Sensitivity of Moments to α

Note: This figure shows how the targeted moments move with α in the model with financial constraints. The rest of the parameters ρ_z, σ_z, and γ are fixed at the estimates in Table 8. The horizontal line indicates $\hat{\alpha} = 0.7169$.

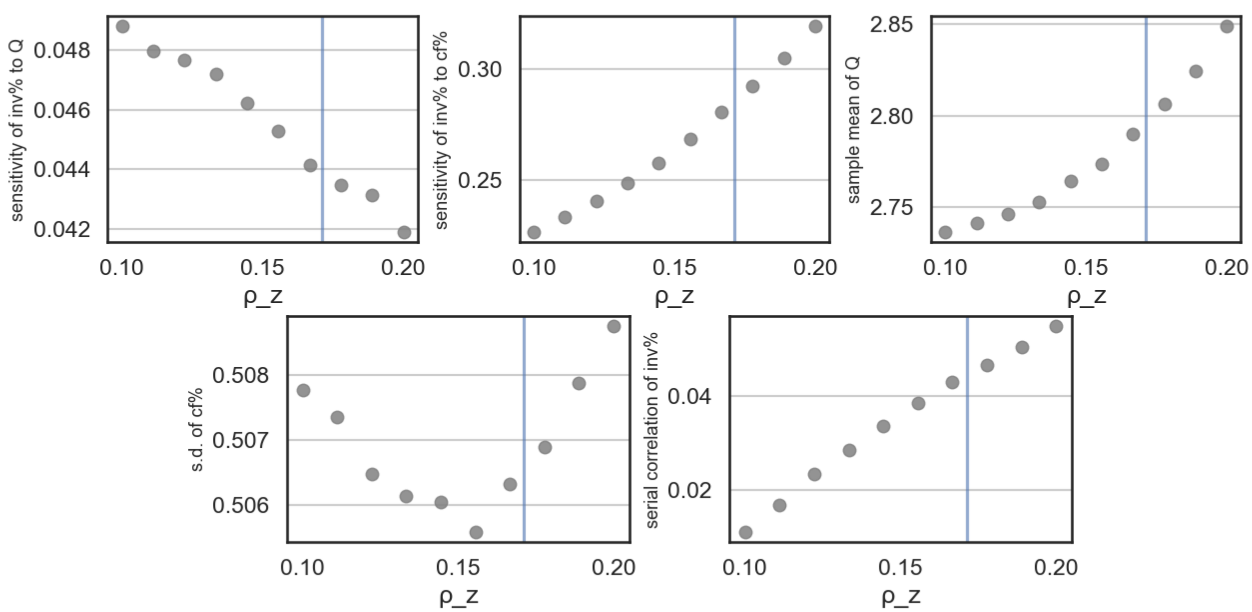


Figure A2: Sensitivity of Moments to ρ_z

Note: This figure shows how the targeted moments move with ρ_z in the model with financial constraints. The other parameters are fixed at the estimates in Table 8. The horizontal line indicates $\hat{\rho}_z = 0.1712$.

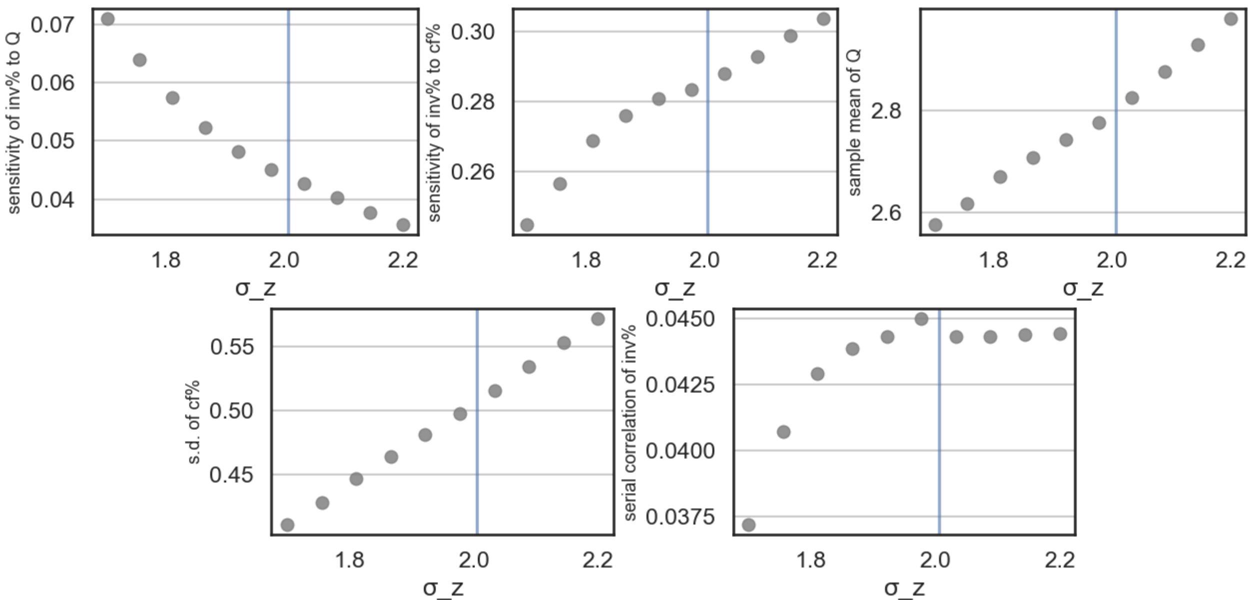


Figure A3: Sensitivity of Moments to σ_z

Note: This figure shows how the targeted moments move with σ_z in the model with financial constraints. The other parameters are fixed at the estimates in Table 8. The horizontal line indicates $\hat{\sigma_z} = 2.0056$.

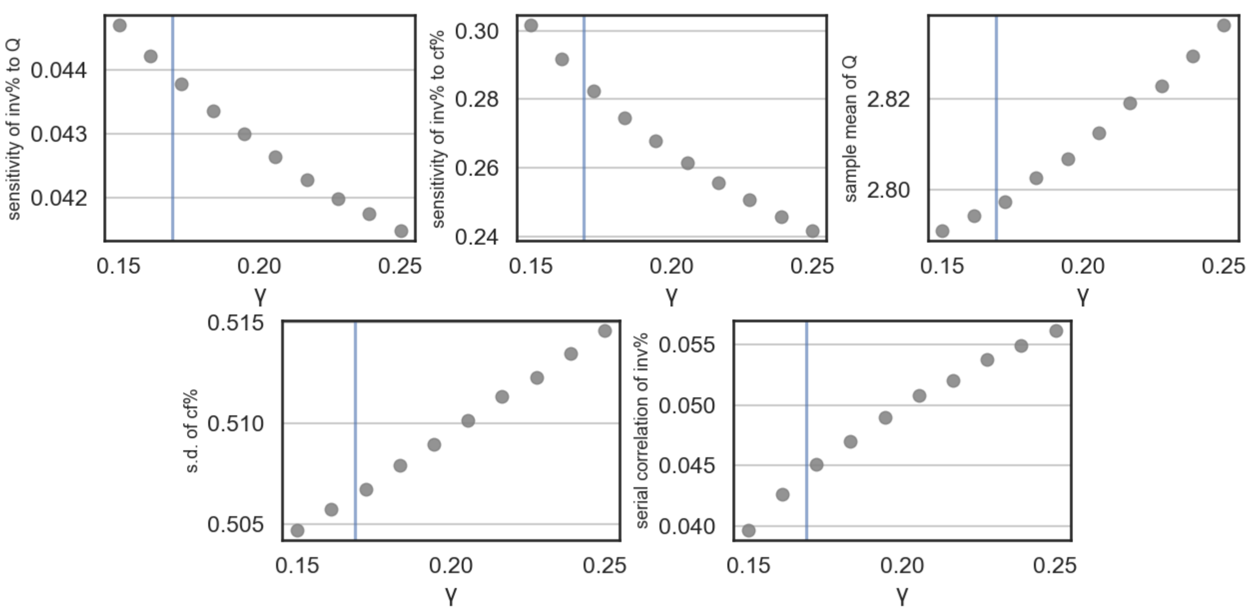


Figure A4: Sensitivity of Moments to γ

Note: This figure shows how the targeted moments move with γ in the model with financial constraints. The other parameters are fixed at the estimates in Table 8. The horizontal line indicates $\hat{\gamma} = 0.1689$.

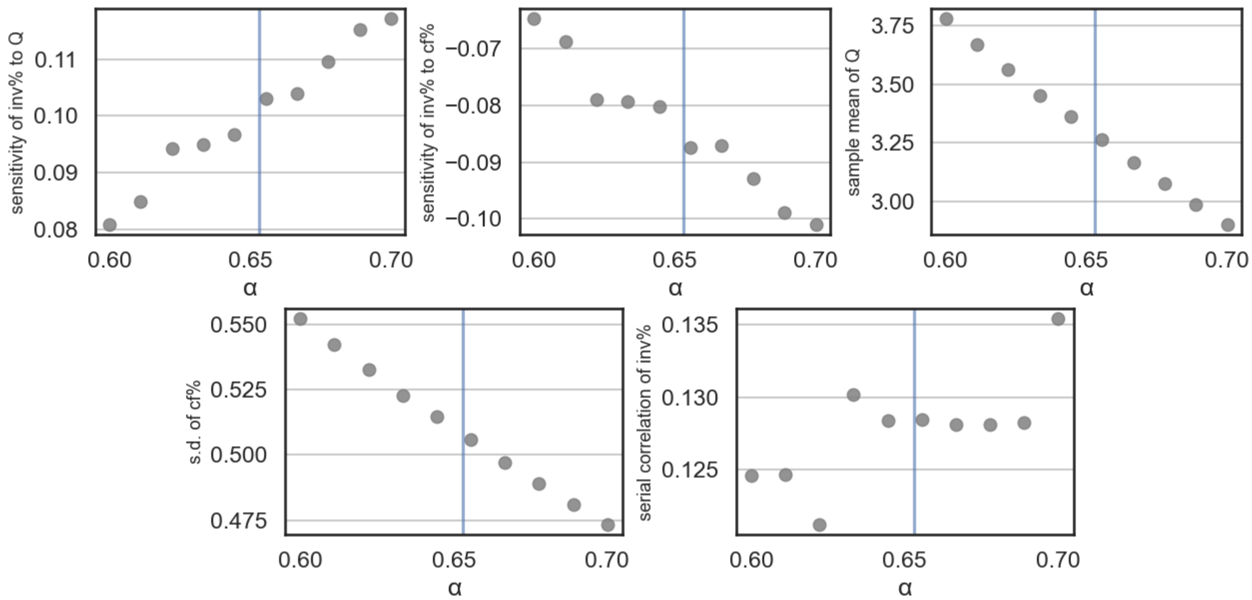


Figure A5: Sensitivity of Moments to α

Note: This figure shows how the targeted moments move with α in the model without financial constraints. The rest of the parameters ρ_z, σ_z, and γ are fixed at the estimates in Table 8. The horizontal line indicates $\hat{\alpha} = 0.6531$.

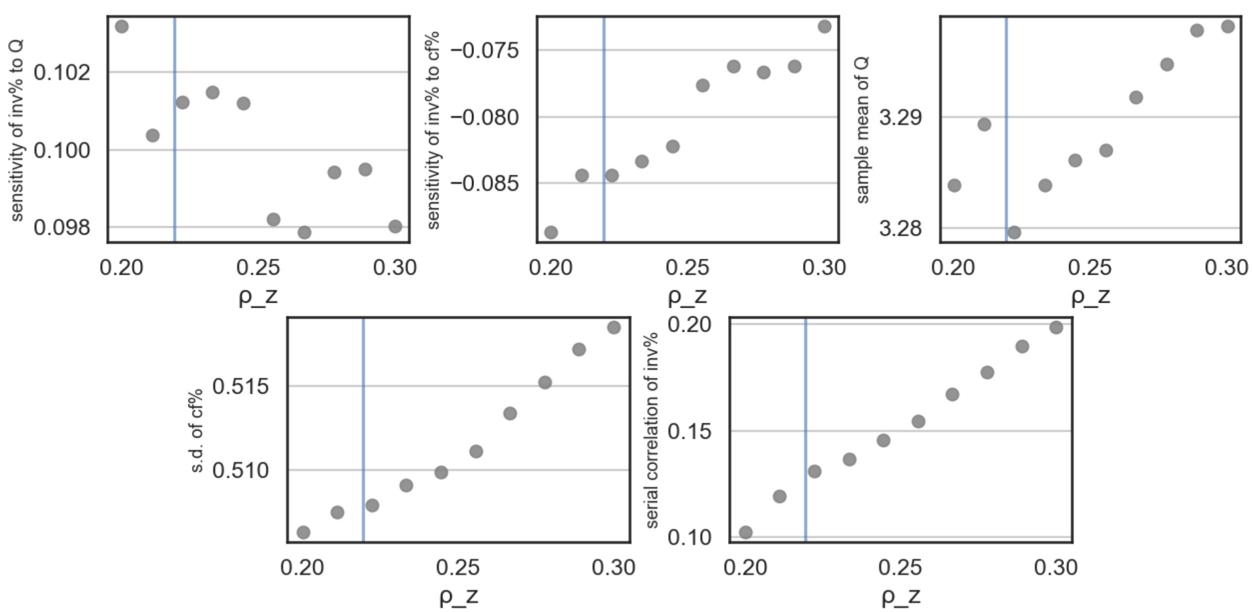


Figure A6: Sensitivity of Moments to ρ_z

Note: This figure shows how the targeted moments move with ρ_z in the model without financial constraints. The other parameters are fixed at the estimates in Table 8. The horizontal line indicates $\hat{\rho}_z = 0.2193$.

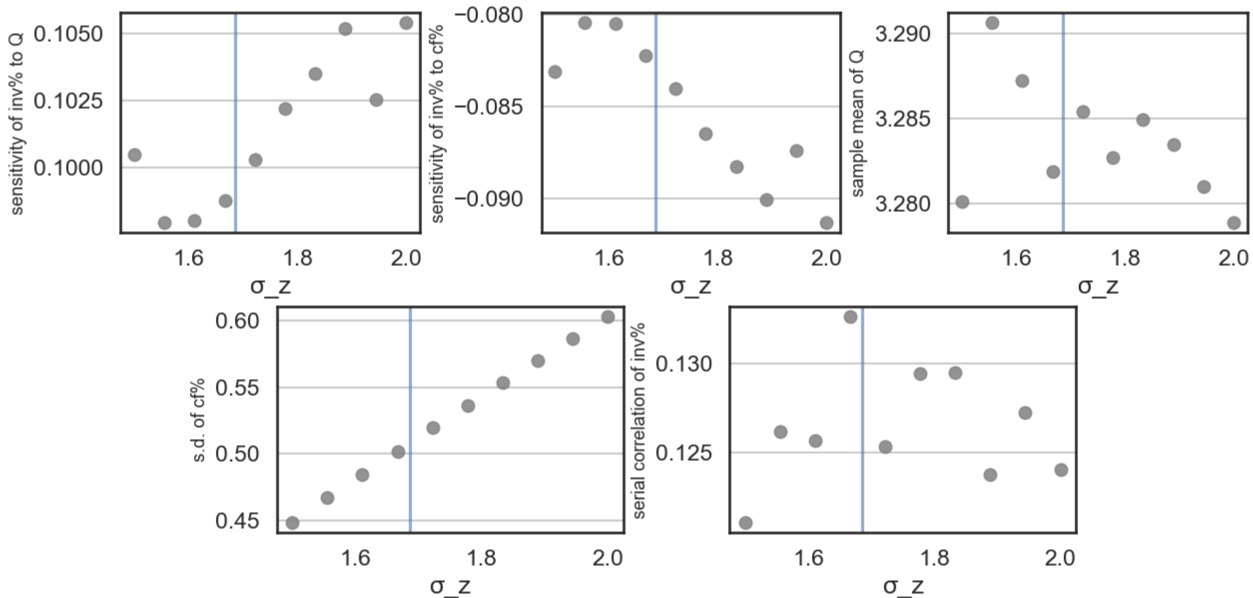


Figure A7: Sensitivity of Moments to σ_z

Note: This figure shows how the targeted moments move with σ_z in the model without financial constraints. The other parameters are fixed at the estimates in Table 8. The horizontal line indicates $\hat{\sigma_z} = 1.6858$.

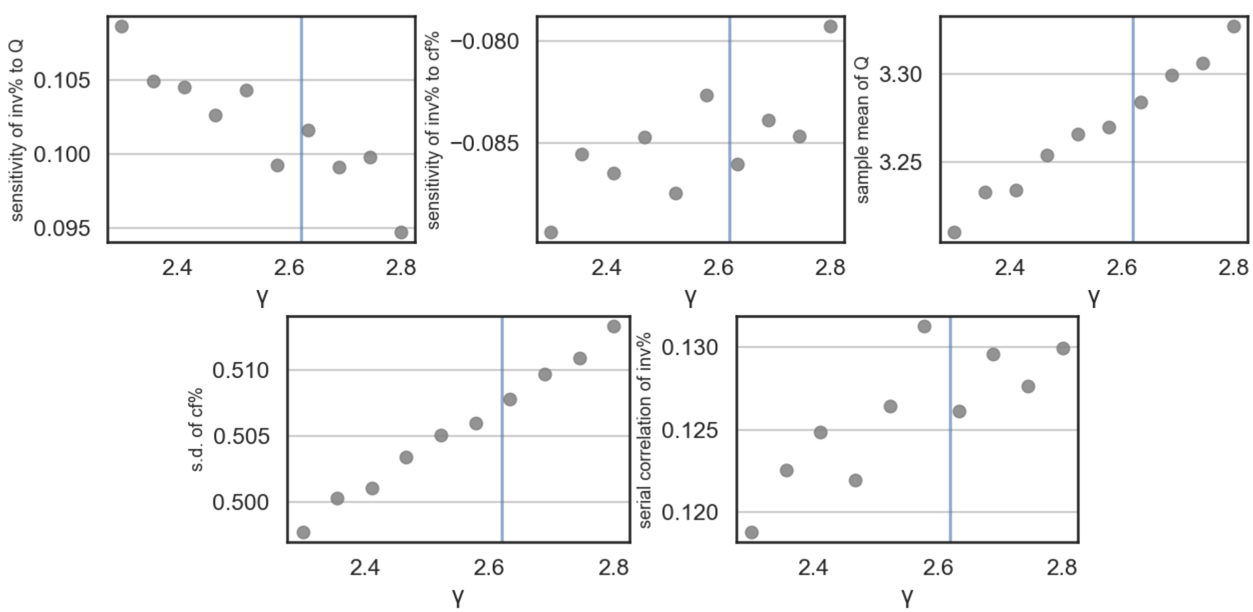


Figure A8: Sensitivity of Moments to γ

Note: This figure shows how the targeted moments move with γ in the model without financial constraints. The other parameters are fixed at the estimates in Table 8. The horizontal line indicates $\hat{\gamma} = 2.6197$.

Table A3: Optimal Weighting Matrix

A. State-owned Firms					
	b_q	b_{cf}	$\overline{ave.Q}$	$std(cf\%)$	$corr(i'\%, i\%)$
b_q	25300				
b_{cf}	712	1240			
$\overline{ave.Q}$	300	25	274		
$std(cf\%)$	1370	763	-251	3100	
$corr(i'\%, i\%)$	-145	-30	-60	-2	5010
B. Private Firms					
	b_q	b_{cf}	$\overline{ave.Q}$	$std(cf\%)$	$corr(i'\%, i\%)$
b_q	45800				
b_{cf}	1650	2200			
$\overline{ave.Q}$	-7	-86	569		
$std(cf\%)$	623	1630	-356	5910	
$corr(i'\%, i\%)$	-1570	201	-195	-158	8020