Investment Frictions and the Aggregate Output Loss in China*

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Abstract

Investment frictions reduce, delay or protract investment expenditure that is necessary for firms to capture growth opportunities. Using an investment model with capital adjustment costs, this article estimates the gap between China's actual and frictionless aggregate output. It applies the method of simulated moments to a fully structural investment model on a panel of Chinese firms and takes into account potential unobserved heterogeneities and measurement error in the data. The estimated capital adjustment costs imply that if Chinese firms had faced a lower level of adjustment costs such as in the US, China's aggregate output would be 25% higher.

I. Introduction

Substantial economic transformation in China has brought strong growth opportunities and a high return to capital (Song, Storesletten and Zilibotti, 2011). In a frictionless environment, firms will optimally respond by increasing their investment expenditure instantaneously and costlessly. However, as in many developing economies, the actual investment behaviour in China might be subject to various frictions, which are caused by a poor investment climate (World Bank, 2005).

Table 1 presents a list of selected indicators based on which the World Bank has constructed the global and subnational Doing Business ranking as a measure of investment climate. Compared with its counterpart in the US, a typical Chinese firm has to spend many more days and pay a much higher cost on starting a business, registering property, getting credit and enforcing contract. Within China, western inland cities like Guiyang and Lanzhou have much poorer indicators than Beijing and Shanghai. Such investment frictions may prevent the instantaneous and costless adjustment of capital stock and potentially make the actual capital stock different from the frictionless benchmark. An under accumulation of capital stock at the firm-level is then translated into a gap between

TABLE 1

Selected indicators for the Doing Business ranking

	US	China		
		National	*Beijing/Shanghai*	*Guiyang/Lanzhou*
Starting a business				
Days to open a business (days)	5	35	37/35	50/47
Cost to open a business (% of income per capita)	0.7	9.3	3.2/3.1	26.6/14.1
Registering property				
Days to register property (days)	12	32	59/29	77/78
Cost to register property (% of property value)	0.5	3.1	3.1/3.6	12.6/7.8
Getting credit				
Strength of legal rights index (0–10)	7	2	n.a.	n.a.
Depth of credit information index (0–6)	6	4	n.a.	n.a.
Days to create and register collateral (days)	n.a.	n.a.	15/8	17/20
Cost to create and register collateral (% of loan value)	n.a.	n.a.	2.7/2.9	6.9/8
Enforcing contract				
Days to enforce contracts (days)	300	292	340/292	397/440
Cost to enforce contracts (% of claim value)	7.7	26.8	9.6/9	23/29.9

Notes: n.a., not applicable. The time and cost of registering collateral were not reported in the global *Doing Business* study. The strength of legal rights index and depth of credit information were not reported in the *Doing Business in China 2008*.

Source: The data for US and China national level are from pages 150 and 105 of World Bank (2007). And the data for cities Beijing, Shanghai, Guiyang and Lanzhou are from pages 38 and 39 of World Bank (2008). See website: `http://www.doingbusiness.org` for more information on the Doing Business ranking.

the actual aggregate output and the first-best aggregate output in an otherwise frictionless environment.

The sharp contrast between strong growth opportunities and large investment frictions motivates the research questions of this article. For a given investment opportunity, how much lower is the aggregate output in China as a result of investment frictions? How much more would Chinese firms invest and produce if they enjoyed a better investment climate, such as the one that prevails in the US? Would firms in underdeveloped regions catch up had they operated in an environment that is typical of more developed areas within China?

The list of frictions that may affect investment is long and complex. As surveyed in Banerjee and Duflo (2005), specific reasons, such as government failure, poorly functioning credit markets and lack of insurance markets, have been examined in the literature. Although each particular friction is of interest, this article aims to understand the quantitative significance of their overall effects. It therefore serves as an important complement to existing research. First, as different frictions may interact, reinforce or offset one another, sometimes it is the total effect that is of the real interest to economists and policy makers. Second, while most research focus on the micro mechanism of specific frictions, this article provides a general approach to quantify their macro impact.

The neoclassical investment model augmented with capital adjustment costs offers a useful framework to investigate our research questions. In a variety of settings, the investment literature has adopted capital adjustment costs to summarize frictional elements that reduce, delay or protract investment (Khan and Thomas, Forthcoming), while the frictionless investment model offers a natural first-best benchmark. Three forms of adjustment cost have been highlighted in this literature: a quadratic adjustment cost, irreversibility and a fixed cost of undertaking any investment (Abel and Eberly, 1994).

Using this framework, the article estimates the effects of investment frictions on aggregate output loss through capital accumulation. The key challenge in this empirical exercise is to separate capital adjustment costs from other factors that may affect investment as well, in particular, the stochastic process that characterizes the investment opportunities. For example, firms in western inland China exhibit lower and more stagnant investment activities compared to their counterparts in eastern coastal region. Is this because these firms have a lower growth rate or because they face higher capital adjustment costs or both? Depending on the answer to this question, the desired policy response could be very different.

To address this identification challenge, this article adopts a fully structural econometric approach. It specifies the complete environment in which investment decisions are taken: the Jorgensonian user cost of capital, production technology, demand schedule, stochastic process and different forms of adjustment costs. The exact investment policies are then solved out for the structural parameters that characterize the environment. These deep or primitive parameters are estimated using a method of simulated moments, which matches simulated model moments with empirical moments from a panel of Chinese firms. This empirical exercise therefore indirectly infers the overall investment frictions facing these Chinese firms, by asking how large the capital adjustment costs must be so as to be consistent with the observed investment behaviour.

The main findings of this article are as follows. First, there are substantial capital adjustment costs for the whole sample. These costs imply that China's aggregate output is 31% below the frictionless benchmark at the steady state. Second, subsample estimation detects significant differences in the quadratic adjustment costs across firms of different sizes and across regions with different investment climates. Keeping all other factors constant, if all the firms in China had faced a lower level of adjustment costs such as in the US, China's aggregate output would be 25% higher. Within China, the output gain could be as large as one-third for small firms and one-quarter for firms in western inland cities.

This research is most closely related to two seminal articles, Cooper and Haltiwanger (2006) and Bloom (2009), in terms of methodology. However, there are three important novelties that are worth highlighting. First, in addition to investment and sales growth rates, this article also matches moments on profit to sales ratio and sales to capital ratio. The information in these two ratios allows the model to flexibly estimate the production technology and demand schedule, which are taken as given in previous research.

Second, although unobserved heterogeneity prevails in micro-level data, it has not been explicitly taken into account by the part of the investment literature using structural estimation. This article models and estimates unobserved heterogeneities in the capital share of the production function and in the growth rate of the stochastic process. Allowing

for such heterogeneities is crucial, both for consistent estimation of the adjustment costs and for accurately quantifying the aggregate output loss.

Finally, one common feature of survey data is the possibility of significant measurement error in recorded variables, especially in stock variables such as capital. This article therefore estimates measurement error in capital stock simultaneously with the true model. It helps to match some important features of the data and hence improves the overall fit substantially.

In the rest of the article, section II outlines the investment model and defines the aggregate output loss. Section III presents the data and introduces the empirical specification. Section IV discusses the identification strategy and the structural econometric approach. Section V reports the empirical results. Section VI estimates the aggregate output loss in China. Section VII discusses the potential limitations.

II. The model

Our analysis is based on a standard model in the investment literature, such as Abel and Eberly (1994). It considers how an ongoing representative firm optimally makes its investment decision, in a partial equilibrium framework where the user cost of capital, production technology, demand schedule and the investment opportunities are all exogenously given. As usual, a static instantaneous operating profit function can first be obtained by optimizing out variable inputs. The intertemporal investment decision is then derived by maximizing the discounted sum of future net profits in the presence of capital adjustment costs.

Production and demand

By paying capital adjustment costs, in each period t new investment I_t contributes to productive capital $\hat{K}_t$ immediately, which depreciates at the end of each period at a constant rate δ. The law of motion for capital stock is therefore

$$K_{t+1} = (1-\delta)(K_t + I_t) \equiv (1-\delta)\hat{K}_t. \tag{1}$$

Consider a firm that uses capital stock $\hat{K}_t$ and a vector of variable inputs L_t (such as labour, material and management) to produce output Q_t^S, according to a stochastic constant returns to scale Cobb–Douglas technology,

$$Q_t^S = A_t \hat{K}_t^\beta L_t^{1-\beta},$$

where A_t represents the randomness in productivity and the capital share β satisfies $0 < \beta < 1$.[1] The firm faces monopolistic competition in the product market. Assume an isoelastic, downward-sloping, stochastic demand curve,

$$Q_t^D = X_t P_t^{-\varepsilon},$$

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[1] As surveyed by Ackerber *et al.* (2007), in the large literature of production function estimation, both in advanced economies such as the US (Blundell and Bond, 2000) and in many developing countries (Söderbom and Teal, 2004), constant return to scale is a specification that is not generally rejected by the data. As labour cost is relatively poorly measured in China, this article only uses information on capital share to estimate β and regulates the share of labour and intermediate inputs as $1 - \beta$ under the constant return to scale restriction.

where X_t represents the randomness in demand; $-\varepsilon < -1$ is the demand elasticity with respect to price.

In any period t, for a given predetermined capital stock, productivity and demand realization, the firm chooses a vector of variable inputs L_t to maximize its operating profit,

$$\pi_t = \max_{L_t} \{Y_t - wL_t\},$$

where $Y_t \equiv P_t Q_t$ denotes sales revenue; $Q_t = Q_t^S = Q_t^D$ is the equilibrium quantity of output produced and sold and w is a constant vector containing the prices of variable inputs.

The first-order condition leads to a constant cost share of variable inputs,[2]

$$\frac{wL_t}{Y_t} = (1-\beta)\left(1-\frac{1}{\varepsilon}\right).$$

Optimization then yields the maximized value of operating profit,

$$\pi_t(Z_t, \hat{K}_t) = \frac{h}{1-\gamma} Z_t^{\gamma} \hat{K}_t^{1-\gamma}, \tag{2}$$

where

$$Z_t = X_t (A_t)^{\varepsilon-1},$$

$$h = (1-\gamma)\left(\frac{\gamma\varepsilon-1}{w}\right)^{\gamma\varepsilon-1} (\gamma\varepsilon)^{-\gamma\varepsilon},$$

and

$$\gamma = \frac{1}{1+\beta(\varepsilon-1)}. \tag{3}$$

The constant cost share of variable inputs implies that the maximized operating profit is also a constant proportion of sales,

$$\frac{\pi_t}{Y_t} = 1 - (1-\beta)\left(1-\frac{1}{\varepsilon}\right) = \frac{1}{\gamma\varepsilon}, \tag{4}$$

so that the maximized sales revenue can be derived from equations (2) and (4):

$$Y_t(Z_t, \hat{K}_t) = \frac{\gamma\varepsilon h}{1-\gamma} Z_t^{\gamma} \hat{K}_t^{1-\gamma}. \tag{5}$$

Following Foster, Haltiwanger and Syverson (2008), this article calls Z_t the revenue total factor productivity (TFPR, hereafter). This is to emphasize that although the stochastic variations in the sales and profit functions could come from both demand X_t and productivity A_t, it is their linear combination $Z_t = X_t(A_t)^{\varepsilon-1}$ that fundamentally determines the

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[2] Bloom (2009) estimates a model using US data with both capital and labour adjustment costs and finds a model without labour adjustment costs can still match key features of the data but a model without capital adjustment costs is strongly rejected. Song and Wu (2013) find that both the capital and labour markets in China are distorted, but the magnitude for capital market distortions is much larger. Therefore, for simplification, this article has assumed that labour is a variable input which can be adjusted without any cost. This does not, however, imply that the labour demand decision has been assumed away. In contrast, given the constant share of labour cost, the aggregate output loss estimated from the article also means the same magnitude of loss in aggregate labour demand, that is a lower level of employment.

marginal revenue product of capital and hence the investment opportunities. This article therefore only models and estimates the stochastic process for Z_t. Assume Z_t is a trend stationary process with growth rate μ and serial correlation ρ. The standard deviation σ of the innovations characterizes the level of uncertainty in this model. That is,

$$
\begin{aligned}
\log Z_t &= \mu t + z_t, \\
z_t &= \rho z_{t-1} + e_t,
\end{aligned}
\tag{6}
$$

where $0 < \rho < 1$, $e_t \overset{\text{i.i.d.}}{\sim} N(0, \sigma^2)$ and $z_0 = 0$.

Investment frictions and capital adjustment costs

In contrast to variable inputs, various investment frictions prevent instantaneous and costless adjustment of the capital stock. To understand the driving force of investment frictions, the World Bank's Doing Business ranking has considered factors in the ease of getting credit, getting electricity, paying taxes, trading across borders, registering property, protecting investors, enforcing contracts, starting a business, dealing with construction permits and closing a business. To provide a modelling mechanism, the investment literature has adopted three forms of capital adjustment costs to capture the effects of various investment frictions on investment behaviour.

Traditionally the investment literature has used quadratic adjustment costs to model certain frictions that lead to a series of gradual and partial adjustment towards targeted capital stock. For example, high cost in getting credit, difficulties in getting electricity, bureaucracies in paying taxes and long delays in trading across borders, all prevent firms from immediately attaining their chosen capital levels. Such frictions can therefore be modelled in the form of quadratic adjustment costs.

Partial irreversibility is another form of adjustment costs that has been widely examined in investment theory. It reflects the adverse selection problem in the second-hand capital goods market, or more generally, the wait-and-see behaviour in investment decisions. For example, difficult property registration, weak investor protection and poor contract enforcement will make firms more conservative in their investment expenditure and sometimes even cause them to do no investment at all.

More recently, fixed adjustment costs have been introduced into the literature to reflect the indivisibility in capital, or more generally, the lumpiness in investment. For example, a high cost of starting a subplant in a new business line, dealing with construction permits for a large investment project, or closing a loss-making subplant, can be modelled as if there are fixed adjustment costs.[3]

Following the functional form in Cooper and Haltiwanger (2006) and Bloom (2009), these capital adjustment costs can be summarized by the adjustment cost function:

$$
G(Z_t, K_t; I_t) = \frac{b_q}{2} \left(\frac{I_t}{K_t} \right)^2 K_t - b_i I_t \mathbf{1}_{[I_t < 0]} + b_f \mathbf{1}_{[I_t \neq 0]} \pi_t,
$$

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[3] There is a large body of literature on the economic rationale for why different forms of capital adjustment costs may be utilized to model the effects of various investment frictions on investment behaviour. Recent surveys include Chirinko (1993), Hamermesh and Pfann (1996) and Khan and Thomas (Forthcoming).

where $\mathbf{1}_{[I_t<0]}$ and $\mathbf{1}_{[I_t\neq0]}$ are indicators for negative and non-zero investment. b_q measures the magnitude of quadratic adjustment costs. b_i reflects the significance of irreversibility and can be interpreted as the difference between the purchase price and the resale price, expressed as a percentage of the purchase price of capital goods. The fixed adjustment cost b_f is interpreted as the fraction of operating profit loss due to any non-zero investment.

Investment decision

Normalizing the price of capital to one, the firm's net profit in each period t is therefore

$$\Pi(Z_t,K_t;I_t)=\pi(Z_t,K_t;I_t)-G(Z_t,K_t;I_t)-I_t.$$

Suppose the owner of the firm discounts future net profits at a constant rate r. The optimal investment problem can be represented as the solution to a dynamic optimization problem defined by the stochastic Bellman equation

$$V(Z_t,K_t)=\max_{I_t}\{\Pi(Z_t,K_t;I_t)+\frac{1}{1+r}E_t[V(Z_{t+1},K_{t+1})]\}, \tag{7}$$

together with the law of motion equations (1) and (6) for K_t and Z_t.

In the benchmark case of no adjustment cost, that is when $G(Z_t,K_t;I_t)=0$, it is straightforward to solve out the the optimal productive capital stock

$$\hat{K}_t^*\equiv(I_t+K_t)^*=HZ_t, \tag{8}$$

and the optimal investment rate

$$\left(\frac{I_t}{K_t}\right)^*=H\left(\frac{Z_t}{K_t}\right)-1, \tag{9}$$

where

$$H=\left(\frac{h}{J}\right)^{\frac{1}{\gamma}}, $$

and

$$J=\frac{r+\delta}{1+r}. \tag{10}$$

Here J is known as the Jorgensonian user cost of capital. Intuitively, without any friction the optimal investment rate $(I_t/K_t)^*$ is a linear function of revenue TFP Z_t relative to inherited capital stock K_t to meet the imbalance between the optimal productive capital stock $\hat{K}_t^*$ and the level of revenue TFP Z_t in each period. This optimality condition also implies a constant frictionless sales to capital ratio

$$\left(\frac{Y_t}{\hat{K}_t}\right)^*=\frac{J}{\beta\left(1-\frac{1}{\varepsilon}\right)}. \tag{11}$$

When $G(Z_t,K_t;I_t)>0$, the optimal investment policy can be solved out using numerical dynamic programming methods. Figures 1(a)–(c) illustrate these policies under different forms of adjustment costs, where the 45 degree lines are plotted as the frictionless
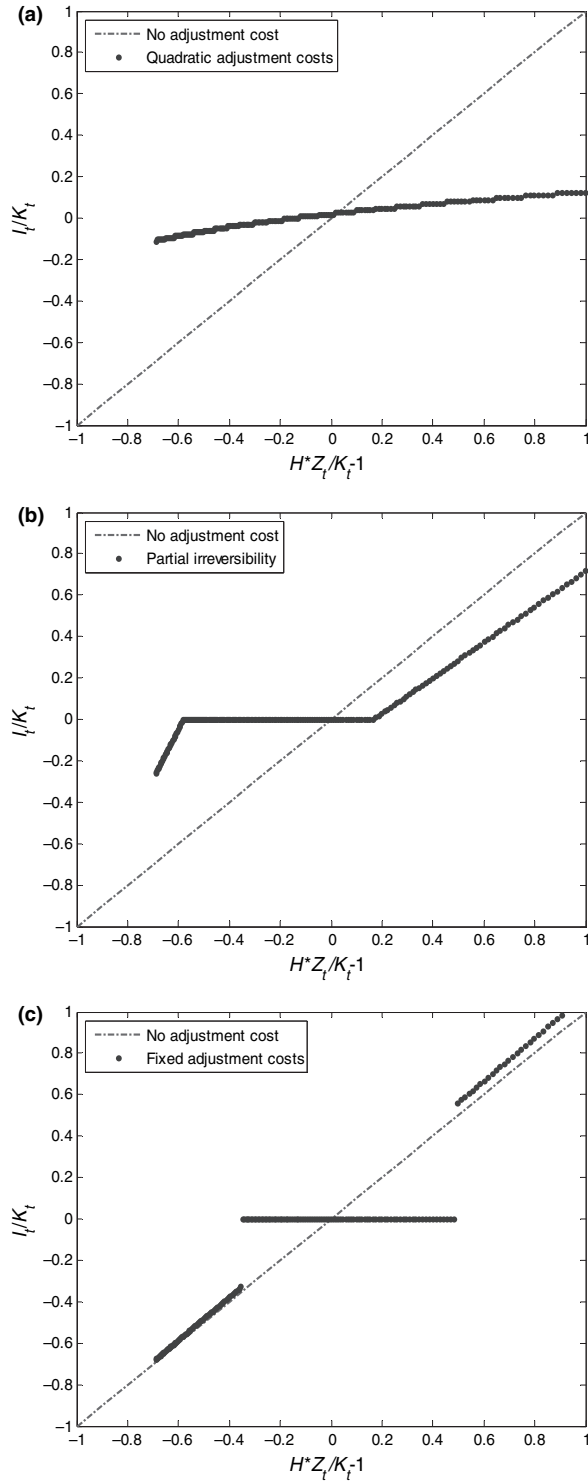
Figure 1. (a) Investment policy for quadratic adjustment costs; (b) investment policy for irreversibility; (c) investment policy for fixed adjustment costs

benchmark equation (9).[4] First of all, irrespective of the form of adjustment costs, the optimal investment policy is always a non-decreasing function of (Z_t/K_t). With respect to each particular form of adjustment costs, when $b_q > 0$, capital accumulation is through a series of small and continuous adjustments. This is consistent with the prediction of the convex adjustment cost literature, such as Abel (1983). When $b_i > 0$, there is a familiar region of inaction in the investment rate as predicted by the irreversibility literature, represented by Dixit and Pindyck (1994), where the optimal investment decision is characterized as a 'barrier control' policy. When $b_f > 0$, lumpiness in the investment rate implies that the optimal investment decision can be characterized as a 'jump control' policy, as documented by Doms and Dunne (1998) in the fixed adjustment cost literature.

The average output loss

Consider a representative firm i in year t. According to equation (5), its actual and first-best sales revenue are $Y_{i,t} = (\gamma \varepsilon h)/(1-\gamma) Z_{i,t}^{\gamma} \hat{K}_{i,t}^{1-\gamma}$ and $Y_{i,t}^{*} = (\gamma \varepsilon h)/(1-\gamma) Z_{i,t}^{\gamma} \hat{K}_{i,t}^{*1-\gamma}$, respectively. Consider an economy with N such firms. Each firm makes optimal investment decision according to the realization of idiosyncratic revenue TFP shocks $e_{i,t}$. Define the average output loss as the differences between $Y_{i,t}$ and $Y_{i,t}^{*}$ averaging across the N firms. The linear homogeneity of the sales function implies that the average output loss is determined by the average differences between $\hat{K}_{i,t}$ and $\hat{K}_{i,t}^{*}$:

$$
\begin{aligned}
\Delta \log \mathbf{Y}_t &\equiv \frac{1}{N} \sum_{i=1}^{N} (\log Y_{i,t} - \log Y_{i,t}^{*}) \\
&= (1-\gamma) \frac{1}{N} \sum_{i=1}^{N} (\log \hat{K}_{i,t} - \log \hat{K}_{i,t}^{*}) \\
&\equiv (1-\gamma) \Delta \log \mathbf{K}_t
\end{aligned}
\tag{12}
$$

For a given Jorgensonian user cost of capital, production technology, demand schedule and a realization of revenue TFP, the frictionless capital stock $\hat{K}_{i,t}^{*}$ can be solved out according to equation (8). In addition to these factors, the actual capital stock $\hat{K}_{i,t}$ also depends on the capital adjustment costs facing the firm. It is such costs at the firm level that are translated into an output loss at the aggregate level.

However, without a closed-form solution to the investment problem in the presence of adjustment costs, it is unclear whether $\hat{K}_{i,t}$ is higher or lower than $\hat{K}_{i,t}^{*}$ and by how much. When $b_i > 0$, Abel and Eberly (1999) demonstrate that irreversibility may increase or decrease capital accumulation due to the opposite user cost effect and hangover effect.[5] When $b_q > 0$, Bond, Söderbom and Wu (2011) show that the capital stock would be

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[4]These figures are simulated under the following parameter values: $h = 1$, $r = 0.10$, $\delta = 0.05$, $\beta = 0.10$, $\varepsilon = 10$, $\rho = 0.9$, $\mu = 0.05$, $\sigma = 0.5$, $b_q = 0.5$, $b_i = 0.25$ and $b_f = 0.025$.

[5]To be specific, the 'user cost effect' occurs because the firm anticipates that the irreversibility constraint may bind in the future and thus is more reluctant to invest today, so that the capital stock under irreversibility is smaller than that under reversibility. The 'hang over effect' indicates the dependence of the current capital stock on past behaviour, especially behaviour that later the firm would like to reverse, which can lead to a higher capital stock under irreversibility than under reversibility.

unambiguously lower than in the frictionless case, because any capital adjustment incurs a cost in addition to the Jorgensonian user cost of capital. If $b_f > 0$, Wu (2009) shows that the effect of fixed adjustment costs on capital accumulation is similar to quadratic adjustment costs under complete certainty and is similar to irreversibility in an uncertain environment. This implies that the effects of adjustment costs on aggregate output loss is in fact an empirical question.

A first-order approximation in a special case

To provide an intuitive example on how capital adjustment costs may cause an output loss, consider a special case when there is quadratic adjustment cost only. That is when $b_q > 0$ and $b_i = b_f = 0$. This special case allows for a closed-form investment Euler equation so that the actual capital stock can be approximated as[6]

$$\hat{K}_{i,t} = \left(\frac{h}{U}\right)^{\frac{1}{\gamma}} Z_{i,t}, \tag{13}$$

where U is the generalized user cost of capital,

$$U \simeq J\left(1 + b_q \frac{I_{i,t}}{K_{i,t}}\right). \tag{14}$$

Comparison between equations (10) and (14) highlights the fact that in the presence of quadratic adjustment costs, the actual user cost of capital is an amplification of the Jorgensonian user cost of capital. The magnitude of the amplification depends on both the quadratic adjustment costs b_q and the investment rate $I_{i,t}/K_{i,t}$. All else being equal, a larger generalized user cost of capital will unambiguously lead to lower capital stock levels.

Together with equations (8) and (13), the average output loss now has a convenient first-order approximation,

$$\Delta \log \mathbf{Y}_t \simeq -\frac{1-\gamma}{\gamma} b_q \frac{1}{N} \sum_{i=1}^{N} \frac{I_{i,t}}{K_{i,t}}. \tag{15}$$

As $\Delta \log \mathbf{Y}_t$ is not observable, it is not possible to estimate b_q from a conventional regression exercise. Instead, $\Delta \log \mathbf{Y}_t$ itself is the quantity of our interest, which depends on the deep or primitive parameters of the investment model, such as γ and b_q. This motivates the structural econometric approach adopted in this article.

The aggregate output loss

The unweighted average output loss in equation (12) is calculated for a representative firm. According to equation (15), this loss will be different for firms with different γ and investment rates. $1 - \gamma$ is the capital coefficient in the sales and profit functions and determines the capital intensity of a firm. Investment rate is a non-decreasing function of the

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[6]The closed-form investment Euler equation is $(1 - \gamma)(Z_{i,t}/\hat{K}_{i,t})^\gamma = (r+\delta)/(1+r) + b_q(I_{i,t}/K_{i,t}) - (1-\delta)/(1+r)b_q E_t(I_{i,t}/K_{i,t}) - (1-\delta)/(1+r)(b_q/2)E_t(I_{i,t}/K_{i,t})^2$. By assuming $E_t(I_{i,t}/K_{i,t}) = I_{i,t}/K_{i,t}$ and omitting the higher order term $(b_q/2)E_t(I_{i,t}/K_{i,t})^2$, one may derive equations (13) and (14).

growth rate μ. To take into account that the actual economy is made of firms with different capital intensities and growth rates, the aggregate output loss is defined as the average of the average output loss across firms with various γ and μ. Thus the ultimate quantity of interest also depends the empirical distributions of γ and μ. As an important contribution to the literature, this article also estimates such distributions using the structural econometric approach.

III. Data and empirical specification

Data

The data set comes from two World Bank Investment Climate Surveys, which were conducted in China in 2001 and 2003 respectively. The combined sample includes 3,948 firms distributed across 15 industries and 23 cities of China. Each firm has 3 years of observations.

The empirical exercise of this article requires five key quantities that are either ratios or growth rates. They are:

(i) investment rate ($I_{i,t}/K_{i,t}$);
(ii) real sales growth rate ($\Delta \log Y_{i,t} \equiv \log Y_{i,t} - \log Y_{i,t-1}$);
(iii) profit to sales ratio ($\pi_{i,t}/Y_{i,t}$);
(iv) log sales to productive capital ratio ($\log(Y_{i,t}/\hat{K}_{i,t})$) as a measure of capital intensity;
(v) log sales to beginning-of-period capital ratio ($\log(Y_{i,t}/K_{i,t})$) as a proxy for the marginal revenue product of capital (MRPK, hereafter).

These quantities are constructed by four key variables that are collected from the data. They are:

(i) investment ($I_{i,t}$): value of investment expenditure net of value of disinvestment in machinery, equipment and plant;
(ii) capital stock ($K_{i,t}$): net book value of machinery, equipment and plant;
(iii) sales revenue ($Y_{i,t}$): total value of sales plus change in inventory of finished goods;
(iv) operating profit ($\pi_{i,t}$): sales net of costs of raw materials and inputs, total energy costs, total labour costs and other overhead costs.

Appendix S1 provides further information about sampling, how these variables are deflated and cleaned, together with the macroeconomic background for China during our sample period.

Figure 2(a) plots the empirical distribution of the investment rate $I_{i,t}/K_{i,t}$. The most distinctive feature is a considerable mass at zero. The second feature is that although the investment rate is highly dispersed, very few firms have negative investment rates. Therefore, there is a striking asymmetry between investment and disinvestment and the distribution is highly skewed to the right. Figure 2(b) illustrates the empirical distribution of the sales growth rate $\Delta \log Y_{i,t}$, and shows that it is also very dispersed. However unlike the investment rate, the distribution of the sales growth rate is much more symmetric, around a mean of approximately 9%. Figure 2(c) is the empirical distribution of $\log(Y_{i,t}/\hat{K}_{i,t})$, which is very similar to that of $\log(Y_{i,t}/K_{i,t})$. Both variables are highly dispersed and distributed symmetrically abound 0.55.
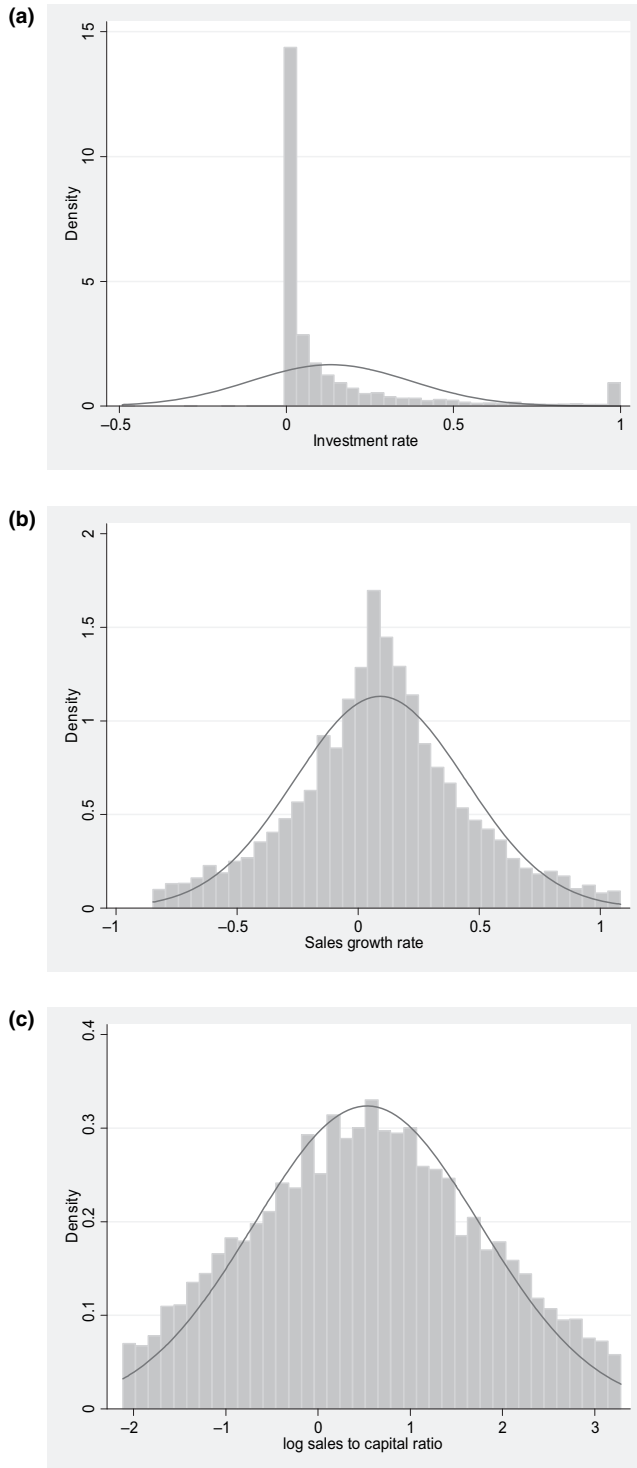
Figure 2. (a) Empirical distribution for investment rate; (b) empirical distribution for sales growth rate; (c) empirical distribution for capital intensity
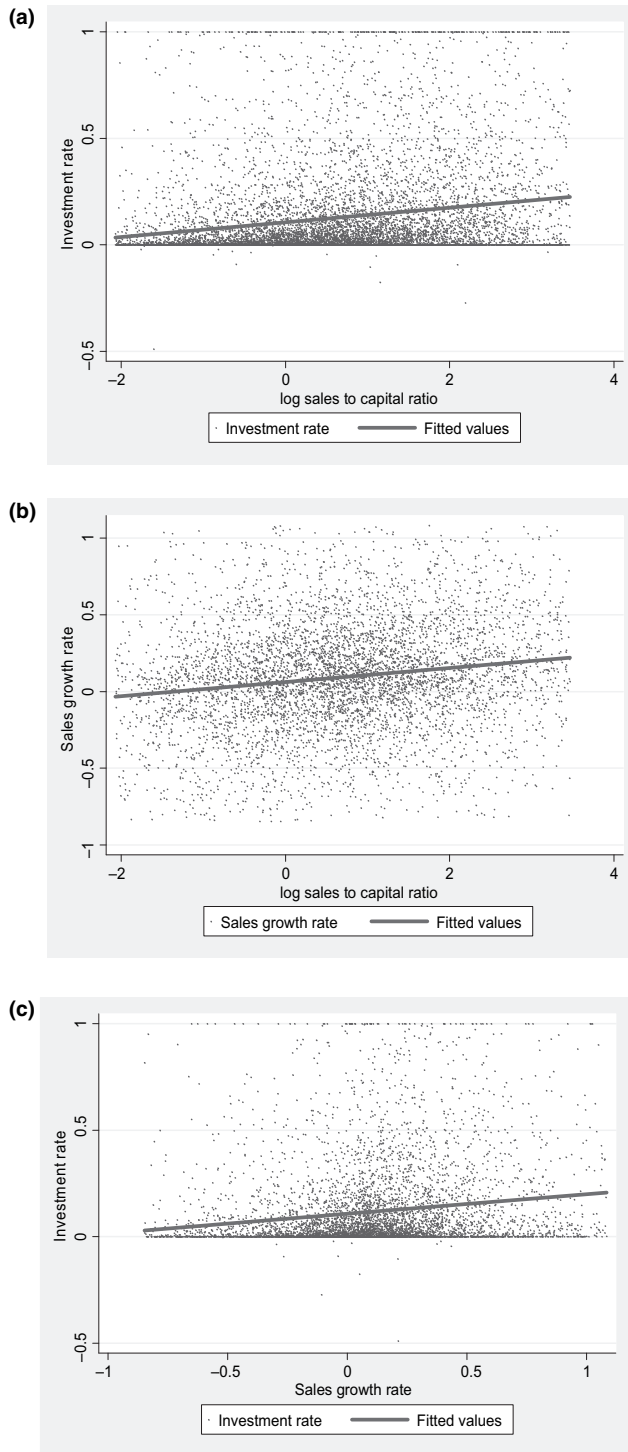
Figure 3. (a) Investment rate versus proxy for MRPK; (b) sales growth rate versus proxy for MRPK; (c) investment rate versus sales growth rate

Figures 3(a)–(c) plot the cross correlations between the investment rate $I_{i,t}/K_{i,t}$, sales growth rate $\Delta \log Y_{i,t}$ and log sales to capital ratio $\log(Y_{i,t}/K_{i,t})$. As highlighted in these figures, both the investment and sales growth rates respond to the proxy of MRPK positively and they are also positively correlated with each other. However, the flat fitted lines also indicate a dampened response and a low correlation, which is consistent with the importance of capital adjustment costs, as simulated in Figures 1(a)–(c).

Empirical specification

Capital share heterogeneity

The first novelty in our empirical specification is to consider potential heterogeneity in the capital share of the production function (β).[7] This is motivated by the following consideration. First, equation (3) implies a one-to-one mapping between β and γ. Hence a heterogeneous β will be translated into a heterogeneous γ. As pointed out in the subsection 'The aggregate output loss' in section II, it is important to match the distribution of γ in order to accurately quantify the aggregate output loss.

Second, firms in this analysis are sampled from various industries which may have different production technology; even within the same industry, the production technology could be firm-specific. Allowing for heterogeneity in β is one way to take into account these firm-specific effects.

Last but not the least, Figure 2(c) highlights the large dispersion in $\log(Y_{i,t}/\hat{K}_{i,t})$ and $\log(Y_{i,t}/K_{i,t})$. Recall that in the absence of adjustment costs $\log(Y_{i,t}/\hat{K}_{i,t})$ would be a constant as in equation (11). Both adjustment costs and heterogeneity in β could cause a dispersion in $\log(Y_{i,t}/\hat{K}_{i,t})$. Therefore, not allowing for potential heterogeneity in β might cause an overestimate of the adjustment costs. Similarly, $\log(Y_{i,t}/K_{i,t})$ has served as a proxy for MRPK so that capital adjustment costs can be inferred by how the investment rate $I_{i,t}/K_{i,t}$ responds to this proxy according to equation (9). As heterogeneity in β will cause dispersion in $\log(Y_{i,t}/K_{i,t})$, both adjustment costs and heterogeneity in β could reduce the correlation between $I_{i,t}/K_{i,t}$ and $\log(Y_{i,t}/K_{i,t})$. This also implies that not allowing for potential heterogeneity in β may overestimate the adjustment costs.

The symmetric empirical distribution of $\log(Y_{i,t}/\hat{K}_{i,t})$ suggests that β can be assumed to be log-normally distributed.

Assumption 1. (Capital share heterogeneity). $\log \beta_i \stackrel{\text{i.i.d}}{\sim} N(\mu_{\log \beta}, \sigma^2_{\log \beta})$. That is each firm i has a firm-specific capital share β_i, where $\log \beta_i$ is drawn independently from an identical normal distribution with mean $\mu_{\log \beta}$ and standard deviation $\sigma_{\log \beta}$.

Growth rate heterogeneity

The second empirical feature taken into account is the potential heterogeneity in the growth rate of revenue TFP (μ).[8] There are three reasons why modelling this heterogeneity is

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[7]All the following arguments also apply to potential heterogeneity in the demand elasticity ε. However, without separate information about the quantity of output ($Q_{i,t}$) and the price of product ($P_{i,t}$), one cannot further distinguish heterogeneity in β from that in ε in this model. Hence we assume homogeneity in demand elasticity and heterogeneity in capital share.

[8]Alternative to modelling heterogeneity in μ, in theory one may also allow for heterogeneity in the serial correlation ρ and the standard deviation σ. This article only allows for heterogeneity in μ due to three reasons. First, μ is the

important. First, and similar to the first motivation of introducing heterogeneity in β, the aggregate output loss should be averaged across firms with different μ.

Second, the empirical exercise pools data across surveys which themselves are spanning across years and regions. Heterogeneity in μ is one way to characterize some year-specific and region-specific effects.

Finally, as recognized in both Cooper and Haltiwanger (2006) and Bloom (2009), a key challenge in estimating adjustment costs is to distinguish permanent differences in the stochastic process from adjustment costs. For example, heterogeneity in μ across firms, as well as high quadratic adjustment costs, can both lead to persistent differences across firms in their investment rates. This also implies that not allowing for potential heterogeneity in μ may cause an overestimation of the quadratic adjustment costs.

The empirical distribution of $\Delta \log Y_{i,t}$ suggests that a normality assumption on the distribution of μ may be appropriate.[9]

Assumption 2. (Growth rate heterogeneity). $\mu_i \overset{\text{i.i.d}}{\sim} N(\mu_\mu, \sigma_\mu^2)$. That is each firm i has a firm-specific revenue TFP growth rate μ_i, where μ_i is drawn independently from an identical normal distribution with mean μ_μ and standard deviation σ_μ.

The investment policy under different (β_i, μ_i) is different. Accordingly, the optimization problem described in equation (7) must be solved for each firm i at each value of (β_i, μ_i), which is infeasible even for a small sample due to the 'curse of dimensionality'. Therefore this article adopts a standard approach used in the literature modelling unobserved heterogeneities, for example, Eckstein and Wolpin (1999), to allow for a finite number of firm types.

Assumption 3. (Finite type of firms). There are 3×3 types of firms, each comprising a fixed proportion $1/(3 \times 3)$ of the population, where the type set is defined as $F = \{(\beta_v, \mu_x): v = 1, 2, 3; x = 1, 2, 3\}$.

Measurement error

In addition to a rich structure of heterogeneities, our empirical specification also allows for potential measurement error in capital stock. This is motivated by two facts. First, measurement errors are common in micro-level data and the capital stock is usually poorly measured. Second and more fundamentally, measurement error in capital stock $K_{i,t}$ will affect key variables such as $I_{i,t}/K_{i,t}$ and $\log(Y_{i,t}/K_{i,t})$. Given capital adjustment costs are inferred from the distribution and dynamics of these ratios, neglecting such measurement error may lead to inconsistency in the estimation.

In reality, the form of measurement error could be very complicated. The specification we consider below has three advantages. First, it guarantees positive values for capital stock.

parameter of interest in quantifying the aggregate output loss. Second, from the view of identification, heterogeneities in μ, ρ and σ all imply a firm-specific stochastic process and are hardly distinguishable from each other. Finally, each parameter with heterogeneity has to be treated as an additional state variable in solving the dynamic programming equation (7). The current model already has four state variables: capital stock K, revenue TFP Z, capital share β and growth rate μ. It would be technically infeasible to estimate a model with additional state variables.

[9] Bloom (2000) shows that, despite the presence of adjustment costs, in the long run both capital stock and sales will grow at the same rate as the revenue TFP in this model. This is essentially because when a firm is on its balanced growth path, the gap between friction and frictionless capital stock is bounded so that $\Delta \log Y_{i,T} \equiv \lim_{T \to \infty} (1/T) \ln(Y_{i,T+t}/Y_{i,t}) = \lim_{T \to \infty} (1/T) \ln(\hat{K}_{i,T+t}/\hat{K}_{i,t}) = \lim_{T \to \infty} (1/T) \ln(Z_{i,T+t}/Z_{i,t}) = \mu_i$.

Second, it does not change the sign of recorded investment rate. Finally, by construction, it does not contaminate identification of other model parameters.

Assumption 4. (Measurement error in capital stock). $K_{i,t} = K'_{i,t} \exp(e^K_{i,t})$, where $e^K_{i,t} \overset{\text{i.i.d}}{\sim} N(0, \sigma^2_{meK})$. Here $K_{i,t}$ denotes the observed capital stock, $K'_{i,t}$ denotes the true underlying capital stock which is not measured accurately in the data. The measurement error has a multiplicative structure, with mean zero and standard deviation σ_{meK}.

The specification tests in Appendix S2 investigate the effects of omitting these innovations, both one by one and all together, on the estimates of other model parameters.

IV. Structural estimation

The structural parameters in the model are estimated by the method of simulated moments (MSM). This methodology has been widely employed in the recent empirical investment literature using micro-level data.[10] Intuitively, the MSM estimates a set of structural parameters by minimizing the quadratic distance between a set of simulated moments from the model and the same set of empirical moments from the data. As different specifications may match some moments more precisely than others, the MSM gives each moment a weight in calculating the quadratic distance, which shares exactly the same idea as GMM. The key point of this methodology is that the value of the simulated moments depends on the structural parameters imposed in each round of simulation. Therefore, if the model is well specified, the distance between the moments is minimized at the optimal estimates of the parameters.

Method of simulated moments

Formally, following Gouriéroux and Monfort (1996), the MSM estimator Θ^* solves

$$\hat{\Theta}^* = \arg \min_{\Theta} \left(\hat{\Phi}^D - \frac{1}{S} \sum_{s=1}^{S} \hat{\Phi}^M_s(\Theta) \right)' \Omega \left(\hat{\Phi}^D - \frac{1}{S} \sum_{s=1}^{S} \hat{\Phi}^M_s(\Theta) \right), \qquad (16)$$

where Θ is the vector of parameters of interest; $\hat{\Phi}^D$ is a set of empirical moments estimated from an empirical data set; $\hat{\Phi}^M(\Theta)$ is the same set of simulated moments estimated from a simulated data set based on the structural model; S is the number of simulation paths and Ω is a positive definite weighting matrix.

Suppose the empirical data set is a panel with N firms and T years. Given the unobserved heterogeneities across firms, the asymptotic results are for fixed T and $N \to \infty$. Denote Ω^* as the inverse of the asymptotic variance–covariance matrix of the empirical moments. When $\Omega = \Omega^*$, that is when the optimal weighting matrix Ω^* is used in solving equation (16), the MSM procedure provides a global specification test of the overidentifying restrictions of the model:

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[10]For example, in addition to Cooper and Haltiwanger (2006) and Bloom (2009), Cooper and Ejarque (2003) and Eberly, Rebelo and Vincent (2008) evaluate the *Q*-model; Bond, Söderbom and Wu (2008) study the effects of uncertainty on capital accumulation; Schündeln (2006), Henessy and Whited (2007) and Bond, Söderbom and Wu (2007) estimate the cost of financing investment; Fafchamps and Söderbom (2006) investigates the dynamic labour demand, all through this structural econometric approach.

$$OI = \frac{NS}{1+S} \left(\hat{\Phi}^D - \frac{1}{S} \sum_{s=1}^{S} \hat{\Phi}_s^M(\Theta) \right)' \Omega^* \left(\hat{\Phi}^D - \frac{1}{S} \sum_{s=1}^{S} \hat{\Phi}_s^M(\Theta) \right) \tag{17}$$
$$\sim \chi^2[\dim(\hat{\Phi}) - \dim(\Theta)],$$

and the MSM estimator is asymptotically normal:

$$\sqrt{N}(\hat{\Theta} - \Theta^*) \xrightarrow{D} N(0, W(S, \Omega^*)), \tag{18}$$

where

$$W(S, \Omega^*) = \left(1 + \frac{1}{S} \right) \left(E\left[\partial \hat{\Phi}^M(\hat{\Theta})' / \partial \Theta \right] \Omega^* E\left[\partial \hat{\Phi}^M(\hat{\Theta}) / \partial \Theta' \right] \right)^{-1}.$$

Identification strategy

The data simulated from this investment model are determined by the following parameters: the Jorgensonian user cost of capital (r, δ), production technology $(\mu_{\log \beta}, \sigma_{\log \beta})$, demand schedule (ε), the serial correlation (ρ), growth rate (μ_μ, σ_μ) and level of uncertainty (σ) of the stochastic process, different forms of adjustment costs (b_q, b_i, b_f) and measurement error (σ_{meK}).

In a model without any heterogeneity and measurement error, by pre-estimating the stochastic process in a first step regression, Cooper and Haltiwanger (2006) indicate that the distribution and dynamics of the investment rate provide identification for capital adjustment costs in the second step structural estimation. Bloom (2009) makes further contribution by showing that it is possible to distinguish the stochastic process and adjustment costs simultaneously when using moments of investment rate and sales growth rate jointly.

To identify the two innovations – namely unobserved heterogeneities and measurement error, this article adopts the following strategy. First, estimate the model using a two-step procedure as in Cooper and Haltiwanger (2006). Second, utilize additional information from the data that has not been employed in existing literature. The first set of information includes moments on profit to sales ratio and sales to capital ratio. According to equations (4) and (11), these two variables could jointly identify the production technology and demand schedule. In particular, the dispersion of sales to capital ratio pins down the unobserved heterogeneity in β.

The second piece of information helps to identify measurement error. It comes from the residue of the following first step regression,[11]

$$\log Y_{i,t} = \alpha + \rho \log Y_{i,t-1} + (1 - \gamma_i) \log \hat{K}_{i,t} - \rho(1 - \gamma_i) \log \hat{K}_{i,t-1} + \eta_i + \xi_{i,t}. \tag{19}$$

This equation is similar to that in Cooper and Haltiwanger (2006), but has two differences due to the new features in the empirical specification. First, the presence of heterogeneity in γ implies this is a heterogenous panel data model. Second, the presence of measurement error implies that the idiosyncratic error term $\xi_{i,t}$ is composed of both the innovations of revenue TFP and the measurement error in capital stock,

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[11]This equation is derived by taking logs on both sides of the sales equation $Y_{i,t} = (\gamma_i \varepsilon h)/(1 - \gamma_i) Z_{i,t}^{\gamma_i} \hat{K}_{i,t}^{1-\gamma_i}$, quasi differencing the logged equation, replacing $\log Z_{i,t}$ and $\rho \log Z_{i,t-1}$ using the AR(1) structure specified in equation (6) and substituting the observed capital stock with the true capital stock and measurement error specified in Assumption 4.

$$\xi_{i,t} = \gamma_i e_{i,t} - (1-\gamma_i)e_{i,t}^K + \rho(1-\gamma_i)e_{i,t-1}^K.$$

To get a proxy for the variance of $\xi_{i,t}$, denote $\bar{\gamma} = (1/N)\sum_{i=1}^{N} 1/(1+\beta_i(\varepsilon-1)))$. We then estimate equation (19) and calculate the variance of the first differenced residual $\mathrm{var}(\Delta\hat{\xi}_{i,t})$.[12] Under the assumption that $e_{i,t}$, $e_{i,t}^K$ and $e_{i,t-1}^K$ are uncorrelated with each other, this imposes a joint restriction on σ and σ_{meK},

$$\mathrm{var}(\Delta\hat{\xi}_{i,t}) = 2[\bar{\gamma}^2\sigma^2 + (1+\rho+\rho^2)(1-\bar{\gamma})^2\sigma_{meK}^2]. \tag{20}$$

Thus, for a given ρ and $\bar{\gamma}$, σ can be inferred from equation (20) for any estimated σ_{meK} in the second step estimation. However, the estimated value of ρ and $\bar{\gamma}$ from equation (19) are subject to attenuation bias due to the presence of measurement error. The benchmark result of the empirical exercises thus imposes $\rho = 0.885$ and $\bar{\gamma} = 0.408$ from Cooper and Haltiwanger (2006).

This identification strategy therefore hinges on two things: first, the value of estimates on ρ and $\bar{\gamma}$; second and more fundamentally, the identification restriction equation (20). In Appendix S2, a robustness test explores the sensitivity of the results by imposing different values on ρ. A specification test examines what happens to the estimates if we use a γ, which is estimated from the Chinese data in the second step estimation. Finally, to investigate the effect of using the identification condition (20), an alternative restriction on noise-to-signal ratio is imposed, when σ_{meK} and σ are estimated simultaneously in the second step estimation.

Although it is difficult to prove identification formally, as illustrated in Whited (2010), a necessary and sufficient condition of identification is that the Jacobian matrix $[\partial\hat{\Phi}^M(\hat{\Theta})/\partial\Theta']$ is of full rank. Intuitively, the precision of the estimates is related to the sensitivity of the moments to movements in the structural parameters through this matrix. If the sensitivity is low, the derivative will be near zero, which will produce a high variance for the structural estimates according to equation (18). Therefore, the standard errors of the estimates provide a useful check for local identification.

Parameters and moments

Column (1) in the upper panel of Table 2 lists the set of parameters Θ to estimate. In addition to these parameters of interest, there are two predetermined parameters in the Jorgensonian user cost of capital $J = (r+\delta)/(1+r)$. The main specification in the empirical results imposes $\delta = 0.03$, which is the difference between the mean of gross capital growth rate and the sales growth rate. The discount rate is set at $r = 0.14$, which is the lower bound of the required rate of return for capital in China estimated in Bai, Hsieh and Qian (2006). Such a high rate of return is consistent with the fact that China is a fast growing economy. The robustness tests in Appendix S2 consider how sensitive the results are to imposing different values for δ and r.

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[12]The cleaned data set is a short panel with 3,618 firms and 3 years. With the presence of firm-specific effect η_i, the equation is estimated using first-differenced GMM methods, where $\log Y_{i,t-2}$ and $\log\hat{K}_{i,t-2}$ are employed as instruments.

TABLE 2

Empirical results for the full sample

Column (1) Definition for parameters	Column (2) Parameters	Column (3)	Column (4) Estimate	Column (5) SE
Quadratic adjustment costs	b_q		1.532	0.122
Irreversibility	b_i		0.370	0.082
Fixed adjustment costs	b_f		0.011	0.005
Demand elasticity	ε		13.953	0.892
Mean of log capital share	$\mu_{log\beta}$		−2.498	0.022
SD of log capital share	$\sigma_{log\beta}$		1.386	0.017
Mean of growth rate	μ_μ		0.087	0.001
SD of growth rate	σ_μ		0.089	0.005
SD of measurement errors	σ_{meK}		0.522	0.003
SD of TFPR shocks (inferred)	σ		0.569*	n.a.

Definition for moments	Moments	Empirical	SE	Simulated
Mean of profit to sales ratio	mean(π/Y)	0.211	0.002	0.218
Mean of capital intensity	mean($\log(Y/\hat{K})$)	0.533	0.020	0.554
Mean of investment rate	mean(I/K)	0.139	0.003	0.151
Mean of sales growth rate	mean($\Delta\log Y$)	0.092	0.005	0.088
SD of capital intensity	SD($\log(Y/\hat{K})$)	1.233	0.011	1.278
SD of investment rate	SD(I/K)	0.256	0.005	0.190
SD of sales growth rate	SD($\Delta\log Y$)	0.353	0.004	0.338
Skewness of capital intensity	skew($\log(Y/\hat{K})$)	0.042	0.023	0.189
Skewness of investment rate	skew(I/K)	2.540	0.065	2.553
Skewness of sales growth rate	skew($d\log Y$)	0.052	0.027	0.048
Serial correlation of capital intensity	scorr($\log(Y/\hat{K})$)	0.852	0.006	0.843
Serial correlation of investment rate	scorr(I/K)	0.428	0.021	0.492
Serial correlation of sales growth rate	scorr($\Delta\log Y$)	0.078	0.023	0.014
How investment rate responds to MRPK	corr(I/K, $\log(Y/K)$)	0.191	0.012	0.407
How sales growth rate responds to MRPK	corr($\Delta\log Y$, $\log(Y/K)$)	0.163	0.014	0.213
How investment rate responds to sales growth	corr(I/K, $\Delta\log Y$)	0.159	0.013	0.446
Proportion of investment spikes	Prop($I/K > 0.2$)	0.253	0.006	0.286
Proportion of investment inaction	Prop($I/K = 0$)	0.295	0.006	0.289
Proportion of disinvestment	Prop($I/K < 0$)	0.002	0.000	0.002
Over-identifying restriction test statistics	OI			1,051

Notes: n.a., Not applicable. Inferred from equation (20) with estimates for σ_{meK}. MRPK, marginal revenue product of capital; *TFPR, revenue total factor productivity.

Column (2) in the lower panel of Table 2 lists the set of moments $\hat{\Phi}^D$ to match. The third column reports the value of these empirical moments estimated from the data, whilst the standard errors are reported in the fourth column. The set of moments includes the means, standard deviations, skewness coefficients, serial correlations and cross correlations between log sales to capital ratio, investment rate and sales growth rate, in addition to the mean of profit to sales ratio and proportions of investment spikes, zero investment and disinvestment. The selection of moments is guided by two principles. First, these moments are effective summary statistics for the important features of the data as illustrated in Figures 2 and 3. Second, the properties of the model discussed in the subsection 'Investment decision' in section II and the empirical specifications discussed in the subsection

'Empirical specification' in section III provide theoretical predictions on how these moments may vary with the structural parameters of our interest, so that jointly this set of moments could potentially identify the parameters listed in the upper panel of Table 2.

V.   Empirical results

The inverse of the variance–covariance matrix of the empirical moments is estimated using a bootstrapping method. This provides a candidate for the optimal weighting matrix in the global specification test equation (17). Michaelides and Ng (2000) find that good finite sample performance requires a simulated sample that is approximately ten times as large as the actual data sample. Therefore, S is set as ten in this empirical exercise. To avoid potential local minima, the minimum quadratic distance problem equation (16) is solved using the simulated annealing algorithm described in Goffe, Ferrier and Rogers (1994). Alternative, starting values for parameters and random draws for TFP shocks have been employed to check the robustness of the results. The dynamic programming equation (7) is solved by the improved policy iteration algorithm (Ljungqvist and Sargent, 2000), taking β_i and μ_i as state variables in addition to Z_t and K_t. Numerical standard errors for the MSM estimator are calculated according to equation (18).[13]

Estimates

Table 2 presents the empirical results for the benchmark model. Column (4) in the upper panel reports the optimal estimates of the structural parameters and column (5) lists the numerical standard errors of these estimates.[14] All three forms of capital adjustment costs are found to be quantitatively important. In particular, $\hat{b}_q = 1.532$ implies a quadratic adjustment cost, which is about 6.5% of the capital stock,[15] evaluated at the sample average. $\hat{b}_i = 0.370$ suggests that the resale price of capital goods is only 63% of the purchase price. $\hat{b}_f = 0.011$ implies any investment or disinvestment would result in a 1.1% loss of operating profit. As about 29.5% observations are at the inaction region of investment, this implies that on average firms are paying a fixed adjustment cost equal to 0.8% of their operating profit.

In their comparable specifications, Cooper and Haltiwanger (2006) estimate $\hat{b}_q = 0.153$, $\hat{b}_i = 0.019$ and $\hat{b}_f = 0.204$; Bloom (2009) finds $\hat{b}_q = 0$, $\hat{b}_i = 0.339$ and $\hat{b}_f = 0.015$. Therefore, compared with similar research using US data, this Chinese data set has predicted a similar size of b_i and b_f as in Bloom (2009), a larger b_i and a smaller b_f than Cooper and Haltiwanger (2006), but a substantially larger b_q than both. Nevertheless, compared with empirical works inferring quadratic adjustment costs from the 'Q-model', for example, Hayashi (1982), where b_q is typically estimated to be around 20, the estimate for b_q in this

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[13] Wu (2009), which is available upon request or via the online Oxford Research Archive, provides further technical details. http://ora.ox.ac.uk/objects/uuid:27e70f50-488a-4113-b7b6-c5b6b916f156.

[14] To evaluate the sensibility of the structural estimates, wherever possible, we compare them with those in the literature. As most of the related research using US data, it should be noted that such comparison is simply to put the numbers in context, as differences in economic structure and development stage should be taken into account.

[15] The size of quadratic adjustment costs as a proportion of capital stock can be calculated as $(b_q/2)E(I_{i,t}/\dot{K}i,t)^2 = (b_q/2)[\mathrm{var}(I_{i,t}/\dot{K}i,t) + (E(I_{i,t}/\dot{K}i,t))^2] = (1.537/2)(0.256^2 + 0.139^2) = 0.065$.

article is in fact much closer to its structural predecessors and is significantly lower than those traditional findings. The specification tests in Appendix S2 investigate the importance of each form of the costs, by imposing zero value for them one by one.

The estimated mean and standard deviation for log β implies that capital share β varies from 0.021 to 0.329 with a median at 0.082. The estimates for both the dispersion and the median value of β are broadly consistent with those in Jorgenson, Gollop and Fraumeni (1987), who use a production function regression based on US data.[16] The median value of β is even closer to that in Pavcnik (2002), who finds that the average of the capital share in the production function across industries is 0.085 for a large sample of Chilean firms, using consistent Olley and Pakes (1996) structural estimates. The estimate for the demand elasticity with respect to price is $\hat{\varepsilon} = 13.953$. According to equation (4), the profit to sales ratio is determined by $1 - (1 - \beta)(1 - (1/\varepsilon))$ in this model. Therefore, for a given β, the value of ε depends on the profitability in the data and is ultimately an empirical question.[17] Together, the estimates for ε and heterogeneous β imply that the capital coefficient in the sales and profit functions $1 - \hat{\gamma}_i$ is 0.516 at the median and varies from 0.210 to 0.810 across the sample.

The estimate for the mean growth rate implies that on average the revenue TFP grows at 8.7% per year. This is consistent with China's real GDP growth rate in the secondary and tertiary industries at the macro level. Meanwhile, the substantial standard deviation of the growth rate may reflect large ups and downs across heterogeneous firms during economic transition. The standard deviation of the measurement error in capital stock is estimated to be $\hat{\sigma}_{meK} = 0.522$ and is statistically significant. This suggests that measurement error in capital stock is indeed an important feature of the data set. According to equation (20), the standard deviation for revenue TFP shocks can be inferred as 0.569, which measures the level of uncertainty in this model. An estimate of $\hat{\sigma} = 0.569$ is between the baseline level of uncertainty (0.413) and high level of uncertainty (0.826) estimated in Bloom (2009) and at the median $\hat{\gamma}\hat{\sigma} = 0.275$ is similar to the level of uncertainty (0.30) estimated in Cooper and Haltiwanger (2006).[18]

Column (5) in the lower panel of Table 2 lists the simulated moments from the model evaluated at the optimal estimates. Comparison between columns (5) and (3) implies that overall the model has provided a reasonably good fit to a large set of empirical moments which describe the level, distribution and dynamics of the key variables. As these moments

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[16] Jorgenson *et al.* (1987) run production function regression over intermediate input, capital input and labour input and report empirical results for different sectors in their table 7.3. Among the 45 US manufacturing and services sectors, the capital share estimate varies from 0.0489 (apparel and other fabricated textile products) to 0.404 (communication services) with a median of 0.115 (motor vehicles and equipment). Such estimate for β should be distinguished from the one in an aggregate production function for value added with capital and labour inputs only, where Jorgenson *et al.* (1987) report a capital share of 0.385 for the US in such an aggregate model in their table 9.8.

[17] For example, Bond *et al.* (2008) find ε is around 24 for a sample of UK manufacturing firms from 1972 to 1991 in the Datastream data set; Song and Wu (2013) estimate ε to be around ten for a sample of US manufacturing firms from 2002 to 2005 in the Compustat data set.

[18] Both this article and Bloom (2009) have assumed a sales function linearly homogeneous in revenue TFP and capital stock such as $Y_t = \text{constant} \times Z_t^\gamma \hat{K}_t^{1-\gamma}$. In contrast, the sales function in Cooper and Haltiwanger (2006) is $Y_t = \text{constant} \times Z_t \hat{K}_t^{1-\gamma}$. All three articles assume a similar law of motion for Z_t. Therefore, the level of uncertainty in our article is directly comparable with that in Bloom (2009) but should be normalized by γ to compare with that in Cooper and Haltiwanger (2006).

are different statistics calculated for different variables, they are by nature of different magnitudes. To evaluate how well a particular simulated moment matches the data, one may compare the distance between the simulated and empirical moments with the standard errors in column (4). While for the majority moments this distance is within three times of the corresponding standard errors, the distance for other moments is much larger, such as how investment rate responds to MRPK. As illustrated in Appendix S2, without introducing unobserved heterogeneities and measurement error, the model would have fit this moment even worse. This points out the direction for further improvement in future research.

Subsample results

Table 3 estimates the same model on several subsamples. We estimate $\text{var}(\Delta \hat{\xi}_{i,t})$ for each subsample in the first-step and impose different values of δ and r, searching along a range of potential values to match each subsample best. These values are reported in the corresponding columns at the bottom of Table 3, together with the number of firms and the median number of employees.

The first sample split is between manufacturing firms and services firms. According to columns (1) and (2), firms in the service sector are more profitable and grow faster on average, however they also face higher quadratic and fixed adjustment costs than their manufacturing counterparts. This could imply that the investment climate of the service sector is worse than that of the manufacturing sector in China. However, this could also be driven by the fact that firms in the service sector are on average much smaller than those in the manufacturing sector.

To study whether there is a significant difference between large and small firms in terms of their adjustment costs, we split the sample at the median number of employees and estimate the model for large firms in column (3) and small firms in column (4). To take into account that the data for large firms might be consolidated across several small subplants within the firm, following Bloom (2009), we assume that the large firms have been aggregated over three small subplants, given their median number of employees is three times as large as that of the whole sample.

The empirical results indicate that in terms of non-convex adjustment costs, large firms face a combination of larger irreversibility and smaller fixed adjustment costs, while small firms face the opposite combination. However, in terms of convex adjustment costs, the estimate for large firms is substantially lower than that of the small firms. If one thinks irreversibility and fixed adjustment costs are two alternative forms of non-convex adjustment costs, the significant difference in the quadratic adjustment costs implies that larger firms face much smaller investment frictions. This finding is consistent with the conventional observation that in developing countries large firms have a more favourable investment climate than small firms, as in Tybout (2000).

To further examine whether differences in capital adjustment costs are informative about the investment environments, we report empirical results for firms in Beijing and Shanghai in column (5) and firms in Guiyang and Lanzhou in column (6). The subnational Doing Business survey on China has highlighted substantial variation in the ease of doing business across geographic regions. Cities in eastern coastal area (such as Beijing and Shanghai) are much more advanced than cities in western inland area (such as Guiyang

TABLE 3

Empirical results for subsamples

	Column (1)	Column (2)	Column (3)	Column (4)	Column (5)	Column (6)	Column (7)
	Full	Manufacturing	Service	Large	Small	BJ&SH	GY&LZ
Parameters							
b_q	1.532	1.278	3.107	0.785	2.487	0.649	2.520
b_i	0.370	0.449	0.103	0.442	0.189	0.437	0.439
b_f	0.011	0.004	0.049	0.008	0.077	0.007	0.040
ε	13.953	16.343	10.502	15.581	12.506	18.792	13.970
$\mu_{log\beta}$	−2.498	−2.499	−2.447	−2.487	−2.430	−2.497	−2.349
$\sigma_{log\beta}$	1.386	1.341	1.394	1.313	1.335	1.342	1.264
μ_μ	0.087	0.077	0.090	0.083	0.094	0.089	0.073
σ_μ	0.089	0.068	0.122	0.076	0.100	0.051	0.074
σ_{meK}	0.522	0.494	0.561	0.470	0.573	0.405	0.557
σ	0.569	0.611	0.501	0.541	0.593	0.622	0.622
Simulated moments							
mean(π/Y)	0.218	0.204	0.246	0.205	0.229	0.198	0.226
mean($\log(Y/\hat{K})$)	0.554	0.506	0.698	0.331	0.838	0.738	0.088
mean(I/K)	0.151	0.122	0.201	0.128	0.178	0.161	0.131
mean($\Delta\log Y$)	0.088	0.078	0.091	0.084	0.094	0.091	0.078
SD($\log(Y/\hat{K})$)	1.278	1.229	1.344	1.226	1.303	1.206	1.231
SD(I/K)	0.190	0.165	0.237	0.165	0.235	0.200	0.160
SD($\Delta\log Y$)	0.338	0.340	0.332	0.342	0.358	0.343	0.340
skew($\log(Y/\hat{K})$)	0.189	0.220	0.186	0.182	0.190	0.159	0.237
skew(I/K)	2.553	2.843	2.200	2.628	2.560	2.434	2.517
skew($d\log Y$)	0.048	0.085	0.063	0.043	0.075	0.154	0.101
scorr($\log(Y/\hat{K})$)	0.843	0.838	0.848	0.852	0.824	0.888	0.807
scorr(I/K)	0.492	0.497	0.476	0.513	0.429	0.467	0.461
scorr($\Delta\log Y$)	0.014	−0.012	0.059	−0.027	0.023	0.016	−0.001
corr(I/K, log(Y/K))	0.407	0.421	0.342	0.402	0.403	0.400	0.389
corr($\Delta\log Y$, log(Y/K))	0.213	0.218	0.177	0.217	0.213	0.248	0.201
corr(I/K, $\Delta\log Y$)	0.446	0.455	0.398	0.472	0.442	0.587	0.350
Prop($I/K > 0.2$)	0.286	0.219	0.397	0.229	0.347	0.307	0.246
Prop($I/K = 0$)	0.289	0.297	0.291	0.213	0.366	0.283	0.321
Prop($I/K < 0$)	0.002	0.002	0.002	0.003	0.001	0.001	0.000
OI	1,051	716	290	430	647	240	56
Other information							
Estimated var($\Delta\xi_{it}$)	0.617	0.581	0.672	0.515	0.731	0.436	0.709
Imposed δ	0.030	0.020	0.060	0.020	0.050	0.040	0.030
Imposed r	0.140	0.150	0.110	0.120	0.160	0.170	0.080
Imposed ρ	0.885	0.885	0.885	0.885	0.885	0.885	0.885
Number of firms	3,618	2,404	1,214	1,806	1,812	553	274
Median employees	112	158	54	331	43	155	77

Notes: BJ, Beijing; GY, Guiyang; LZ, Lanzhou; SH, Shanghai.

and Lanzhou), with respect to their financial development, investment infrastructure and business regulations among others. Therefore, one would expect a much better investment climate in Beijing and Shanghai, compared with that in Guiyang and Lanzhou.

The estimates for these two subsamples are indeed consistent with this prior belief. With similar size of irreversibility, the estimates for both quadratic and fixed adjustment costs

are substantially larger for firms in Guiyang and Lanzhou than for firms in Beijing and Shanghai. On average, firms in Guiyang and Lanzhou are paying a quadratic adjustment cost which is 9.43% of their capital stock and a fixed adjustment cost which is 2.6% of their operating profit. In contrast, the corresponding cost proportions are only 2.8% and 0.48% for firms in Beijing and Shanghai.

VI.   Aggregate output loss in China

The estimated structural model provides a useful framework to quantify the effects of capital adjustment costs on forgone aggregate output. This section simulates the changes in aggregate output by varying the estimated capital adjustment costs to the ideal values and keeping all other factors constant. Such exercises are by nature comparative static analyses. Appendix S3 provides a discussion on the effects of other factors, which have been assumed constant and exogenous in the model, on our empirical findings.

The gap between actual and first-best output

Table 4 simulates the effects for the whole sample according to equation (12). Recall that, there are heterogeneities in both β and μ. The heterogeneity in β implies the heterogeneity in γ by equation (3). These effects are therefore simulated for different types of firms along $1 - \gamma$, the capital coefficient in the sales and profit functions and μ, the growth rate of the revenue TFP. The aggregate output loss is the average value of these effects along these two dimensions.

On average, the actual aggregate capital stock is 61.3% lower than the frictionless level. Given that on average the log capital stock counts for 51.2% in the log output, the actual aggregate output is 31.4% lower than the frictionless benchmark. Across different types of firms, for a given level of growth rate, the losses in average capital stock increase with the capital coefficient. For a given level of capital coefficient, the losses in average capital stock increase with the growth rate. Both of them are consistent with the prediction of equation (15).

To further study the relative importance of different forms of adjustment costs, Table 5 reports the aggregate output loss when there are only quadratic adjustment costs, irreversibility and fixed adjustment costs, respectively. The finding is that, although irreversibility and fixed adjustment costs also generate a sizeable loss, it is the presence of the quadratic adjustment costs that contributes most to the forgone output.[19]

To check the validity of the first-order approximation derived in the subsection 'A first-order approximation in a special case' in section II, consider firms which have a median level of γ and μ. As the average investment rate is 0.151 and b_q is estimated at 1.532 for the full sample, equation (15) predicts an aggregate output loss of around 22.5%. This is very close to the magnitude simulated in the fifth row of Table 4. Recall from the specification tests, had we not allowed for unobserved heterogeneities or measurement error, the model would

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[19] One way to rationalize the importance of quadratic adjustment costs is through financial frictions, see Wang and Wen (2012) for an example.

TABLE 4

Aggregate output loss in China

Type	Heterogeneities	$1-\gamma$	μ	$\Delta logK$	$\Delta logY$
1	Low capital intensity, low growth rate	0.210	−0.002	−0.254	−0.054
2	Low capital intensity, median growth rate	0.210	0.087	−0.258	−0.054
3	Low capital intensity, high growth rate	0.210	0.176	−0.392	−0.082
4	Median capital intensity, low growth rate	0.516	−0.002	−0.440	−0.227
5	Median capital intensity, median growth rate	0.516	0.087	−0.442	−0.228
6	Median capital intensity, high growth rate	0.516	0.176	−0.604	−0.312
7	High capital intensity, low growth rate	0.810	−0.002	−0.842	−0.682
8	High capital intensity, median growth rate	0.810	0.087	−0.934	−0.757
9	High capital intensity, high growth rate	0.810	0.176	−1.349	−1.092
Average		0.512	0.087	−0.613	−0.314

TABLE 5

Effects of different forms of adjustment costs

b_q	b_i	b_f	$\Delta logK$	$\Delta logY$
1.532	0.000	0.000	−0.576	−0.295
0.000	0.370	0.000	−0.096	−0.049
0.000	0.000	0.011	−0.022	−0.011
1.532	0.370	0.011	−0.613	−0.314

TABLE 6

Loss and gain in China using US as counterfactual

Type	Heterogeneities	$1-\gamma$	μ	$\Delta logK$	$\Delta logY$	$\Delta\Delta logY$
1	Low capital intensity, low growth rate	0.210	−0.002	−0.072	−0.015	0.038
2	Low capital intensity, median growth rate	0.210	0.087	−0.036	−0.007	0.047
3	Low capital intensity, high growth rate	0.210	0.176	−0.053	−0.011	0.071
4	Median capital intensity, low growth rate	0.516	−0.002	−0.141	−0.073	0.154
5	Median capital intensity, median growth rate	0.516	0.087	−0.081	−0.042	0.186
6	Median capital intensity, high growth rate	0.516	0.176	−0.082	−0.042	0.270
7	High capital intensity, low growth rate	0.810	−0.002	−0.307	−0.249	0.433
8	High capital intensity, median growth rate	0.810	0.087	−0.154	−0.125	0.632
9	High capital intensity, high growth rate	0.810	0.176	−0.157	−0.127	0.965
Average		0.512	0.087	−0.120	−0.062	0.252

have estimated even larger quadratic adjustment costs, and hence a even more substantial loss.

Counterfactual simulations

Taking the estimated structural model as a laboratory, controlled experiments can be conducted to investigate hypothetical questions. For example, how would the aggregate output loss differ, if Chinese firms faced the same level of frictions as US firms? Table 6 thus simulates the effects of adjustment costs for China by imposing its b_q, b_i and b_f to be the corresponding values estimated from Bloom (2009), keeping all other factors constant. It indicates that the aggregate output loss would be 6.2% only. The last column of Table 6

takes the differences between the aggregate output loss in China using the first-best and US as benchmark, respectively. It thus implies that averaging across different types of firms, a reduction in frictions down to the US level would generate a 25.2% increase in China's aggregate output.

Similar exercises are implemented to simulate the gains for small firms using large firms the benchmark and for firms located in Guiyang and Lanzhou, using firms in Beijing and Shanghai as the benchmark. Within China, if the small firms had operated in a better environment as implied by the lower level of adjustment costs faced by their large counterparts, their aggregate output would be 34.2% higher. Aggregate output gain would also be substantial, as large as 24.8%, had firms in Guiyang and Lanzhou faced the lower frictions that their counterparts in Beijing and Shanghai enjoyed.

VII.   Conclusion

Over the past decade, China has been consistently ranked only around 90th out of 180 economies in terms of the overall ease of doing business (World Bank, 2007). Even within China, the ease of doing business varies greatly across cities (World Bank, 2008). Using an investment-capital adjustment costs framework, this article indirectly infers the aggregate output loss in China caused by a poor investment climate. The estimated substantial output gain by improving the investment climate to the US benchmark gives a quantitative measure of 'how bad the investment climate is in China'. The subsample estimates also find much higher quadratic adjustment costs in cities with lower Doing Business ranking than those with higher ranking. Although investment frictions and capital adjustment costs are abstract and not observable directly, the Doing Business ranking is constructed based on specific indicators and is easily available. Therefore, the consistency between the estimates of capital adjustment costs and the Doing Business ranking implies the importance of improving lagged indicators identified in the Doing Business ranking in order to reduce aggregate output loss.

Despite these interesting and important findings, this article has several caveats that need further investigation. First, instead of making a one-to-one correspondence between capital adjustment costs and the specific factors in the Doing Business ranking, this article takes capital adjustment costs as a generic representation of various investment frictions, so as to quantify their overall effects. This complements other researches which aim to give more detailed policy advice, by estimating the impact of particular frictions. For example, Bond *et al*. (2007) study how costly external finance may affect capital accumulation for firms in Brazil and China.

Second, there has been a recent debate in the development and economic growth literature, for example, Easterly and Levine (2001), on whether it is factor accumulation or TFP that is more important for economic growth. The finding of this article is in line with a vast literature emphasizing the importance of capital accumulation, for China as in Ding and Knight (2011) and for many economies in general as in Bond, Leblebicioglu and Schiantarelli (2010). However, this does not necessarily imply the insignificance of TFP. The high growth rate of revenue TFP estimated from the model is taken as exogenous in this article. Estimating an investment model with endogenous TFP growth will be an interesting task for future research.

Finally, like most researches on capital adjustment costs, the analysis in this article is partial equilibrium in nature. Therefore the magnitudes estimated in this article are subject to potential general equilibrium effects. To fully address the aggregate output loss in a general equilibrium framework, one has to develop a dynamic stochastic general equilibrium model to reflect the complex interaction between TFP shocks, endogenous factor prices and capital adjustment dynamics. Furthermore, the choice of production technology may be endogenous and the market structure may evolve in a more general setup. Such analysis is certainly important but is beyond the scope of this article.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Data
Appendix S2. Specification tests and robustness tests
Appendix S3. The effects of other factors