A Structural Estimation on Distortions in UK and Chinese Manufacturing Firms

Zheng Michael Song* and Guiying Laura Wu†

March 18, 2011

Abstract

How much the cross country differences in output per capita is attributed to differences in capital accumulation or to TFP is a subject of great controversy. This paper provides quantitative assessment for these two hypotheses using firm level data from UK and China. It models heterogeneity in the capital goods prices to capture a generic family of distortions that would lead to aggregate TFP loss, and allows for different forms of capital adjustment costs to summarize investment frictions that may affect capital accumulation. Our identification strategy allows for many unobserved heterogeneities and measurement errors, which are crucial for consistent estimation for both factors. Counterfactural simulations indicate that on average reducing the dispersion of capital goods prices to the UK level would enhance aggregate TFP by 20% in China, and moving the capital adjustment costs to the UK level would increase capital stock by 5% in China, which respectively contribute to two-thirds and one-third increase in aggregate output. We find that small, private-owned firms without political connection in east China face unfavorable distortions.

JEL Classification: E22, D92, C15

Key Words: distortion, capital adjustment costs, unobserved heterogeneities

*Chinese University of Hong Kong; Email: zsong@cuhk.edu.hk.

†Nanyang Technological University; Email: guiying.wu@ntu.edu.sg.

1 Introduction

Understanding the large and persistent differences in output per capita across countries has been the central theme in growth theory and development economics for a long time. The macro-growth literature typically assumes a homogeneous aggregate production function such as the Solow model. By testing the beta convergence, a large empirical literature on economic growth, represented by Mankiw, Romer and Weil (1992) and Barro and Sala-I-Martin (1995), suggests the crucial role of aggregate capital accumulation in less developed economies catching up the developed ones. In contrast, extensive evidence from the micro-development literature, as surveyed in Banaerjee and Duflo (2005), has found enormous heterogeneity of rates of return to the same production factors within a single economy. Hsieh and Klenow (2009) calculate that reallocating factors to equalize marginal revenue products to the extent observed in the U.S., the total factor productivity (TFP) would increase 30-50% in China and 40-60% in India. Not surprisingly, how much the cross country differences in output per capita is attributed to differences in capital accumulation or to TFP remains a subject of great controversy.

This paper provides quantitative assessment for these two hypotheses using firm level data from China and UK. Investment in practice is subject to various constraints. Some of these constraints are common to all the firms within the same economy. For example, a less developed financial market compared to that in UK implies more investment frictions faced by all firms in China. Other constraints may be firm specific due to idiosyncratic distortions in policies and institutions. For example, the state-owned banking system in China may offer different interest rates on loans based on ownership of each particular firm. A long list of various frictions and distortions has been well documented in the recent growth and development literature. Although understanding each specific channel is interesting and important, the focus in this paper is to estimate the overall significance of frictions on capital accumulation and distortions on TFP.

To achieve this goal, we estimate a dynamic neoclassical investment model that incorporates homogeneous capital adjustment costs and heterogeneous capital goods prices. This model offers a useful economic laboratory to study the two potential sources of cross country differences in output per capita. On the one hand, in a variety setting, capital adjustment costs have been adopted by the investment literature to summarize frictional elements that reduce, delay or protract investment (Khan and Thomas, 2006), while the frictionless investment model offers a natural benchmark where capital accumulates instantaneously and costlessly according to changes in economic conditions. On the other hand, idiosyncratic distortions which create wedges in the marginal revenue product of capital across firms can lead to a loss in the aggregate TFP (Restuccia and Rogerson, 2008). Investment optimality implies the equality between the marginal revenue product of capital and the user cost of capital for each firm. Hence modelling capital goods price heterogeneity captures a generic family of distortions of this type.

Our estimation approach is fully parametric and structural under this framework. For given aggregate relative prices, the model we consider specifies the complete environment in which investment decisions are taken: the user cost of capital, production technology, demand schedule, the stochastic process characterizing growth and uncertainty, and different forms of capital adjustment costs. Structural parameters are estimated using a method of simulated moments (MSM) by matching simulated model moments with empirical moments from panels of UK and Chinese manufacturing firms. The estimated investment model matches important features of profit-to-sales ratio, log sales-to-capital ratio, investment rate and sales growth rate in their distribution and dynamics. Counterfactual simulations indicate that on average moving the capital adjustment costs to the UK level would increase aggregate capital stock by 5.3% in China, which contributes a 3.5% increase in aggregate output. Reducing the dispersion of capital goods price to the UK level would enhance aggregate TFP by 20.1% in China and this is translated into a 6.9% aggregate output increase.

This paper is closely related to the recent growing literatures on misallocation. Among others, Hsieh and Klenow (2009) offers a seminal framework in which the negative effect of distortions on aggregate TFP can be summarized by the dispersion of log sales-to-capital ratio. However, an investment model with homogeneous frictions, such as non-convex capital adjustment costs, financing constraints or uninsurable investment risk, can only account for less than 10% dispersion in the data, as highlighted by Midrigan and Xu (2009). This big gap between the model and the data motivates us to model and estimate idiosyncratic distortions in the form of heterogeneous capital goods prices, whose dispersion can be directly translated into aggregate TFP loss.

Our assumption of idiosyncratic capital goods prices in an investment model is equivalent to the idiosyncratic rental cost of capital in a rent model such as in Hsieh and Klenow (2009). However, as indicated by the first order condition of the investment model, in addition to the heterogeneity of capital goods prices, the dispersion of log sales-to-capital ratio can also be caused by the heterogeneity of capital share in production or demand elasticity, measurement errors in the data and capital adjustment costs, which are indeed well-recognized in Hsieh and Klenow (2009).

We contribute to this identification challenge with three designs. First, we use dispersion of profit-to-sales ratio and log sales-to-capital ratio jointly to estimate the unobserved heterogeneity in the capital share in production. We find big dispersion in this dimension in both UK and China. A model missing such heterogeneity would overestimate the heterogeneity in capital goods prices, while the magnitude of aggregate TFP loss depends positively on the share of capital in the production. Second, we separate the between-group dispersion from the within-group dispersion of these two variables. Together with their own serial correlation, the model pins down the measurement errors in capital, sales, and profit. We do find greater measurement errors in the Chinese data than in the UK. Finally, we match moments which characterize the first order condition of optimal investment to estimate capital adjustment costs. We find a model missing capital adjustment costs would underestimate the dispersion in capital goods prices.

Nevertheless, even after controlling for all these potential concerns, we still find significant heterogeneity in the capital goods prices in China, which is about 1.6 times as that in UK. All else being equal, if one interprets the log sales-to-capital ratio as an informative indicator on capital goods prices, firms that are small, private-owned, locate in east area and have no political connection in our Chinese sample are found to have faced significantly higher capital goods prices than their counterparts. Therefore aggregate TFP and aggregate output would be substantially enhanced if policy and institutional distortions were alleviated so that more capital was reallocated towards these firms. Such policy experiment is consistent with the explanation on why China has been growing so fast as in Zilibotti, Storesletten, and Song (2010).

This paper also contributes to the estimation and properties of the investment-capital adjustment costs literature. In terms of estimation, Cooper and Haltiwanger (2006) and Bloom (2009) first adopt the MSM to recover structural parameters of capital adjustment costs. Similar to their findings, we show that a mix of quadratic adjustment costs and irreversibility matches our firm-level data best. However, beyond simply estimating an investment-capital adjustment costs model, this paper first explicitly models and estimates unobserved heterogeneities and measurement errors using the structural approach. Specification tests indicate that ignoring such heterogeneities or measurement errors would lead to a severe upward bias in the estimates of adjustment costs.

Regarding the effect of capital adjustment costs on capital accumulation, we find although irreversibility is crucial in generating a sizeable investment inaction in the data, it is the quadratic adjustment costs that reduce the capital stock. This empirical finding is consistent with the interesting properties demonstrated in Abel and Eberly (1999) that irreversibility may increase or decrease capital accumulation due to the opposite user cost effect and hangover effect. In contrast, as pointed out in Bond, Söderbom and Wu (2011), the presence of quadratic adjustment costs unambiguously increases the user cost of capital hence leads to lower capital stock than otherwise. Indeed, even at the same aggregate relative prices, our investment model predicts more capital accumulation in China if its quadratic adjustment costs were reduced to the level of UK. Economic reforms that bring a better investment climate for everyone would therefore stimulate more capital accumulation (World Bank, 2005).

The rest of the paper is organized as follows. Section 2 outlines the investment model and explains the measures for losses in aggregate TFP and capital stock. Section 3 presents the data and our empirical specification. Section 4 discusses identification and reports the empirical results. Section 5 provides the counterfactual simulations and links our findings to observable firm characteristics. Section 7 concludes.

2 The Model

2.1 Production and Demand

Consider an economy made of N existing firms. Each firm hires homogeneous capital goods and variable inputs (materials, labor and managers) from the factor markets, produces one single final good and is the monopolist in its product market. Competition in factor markets leads to common capital goods price P^K and variable inputs price w across all the firms. Monopoly power in the product market implies non-zero profit.

To be more specific, firm i in year t uses productive capital stock $\widehat{K}_{i,t}$, and a vector of variable inputs $L_{i,t}$ to produce $Q_{i,t}$ unit of product i, according to a stochastic constant returns to scale Cobb-Douglas technology,

$$Q_{i,t} = A_{i,t}\widehat{K}_{i,t}^{\beta_i}L_{i,t}^{1-\beta_i}$$

where $A_{i,t}$ represents the randomness in productivity; the capital share β_i satisfies $0 < \beta_i < 1$.

Each product i is demanded in a monopolistic product market according to an isoelastic, downward-sloping, stochastic demand curve

$$Q_{i,t} = X_{i,t}P_{i,t}^{-\varepsilon_i}$$

where $X_{i,t}$ represents the randomness in demand; $-\varepsilon_i < -1$ is the demand elasticity with respect to price.

At each year, for a given predetermined capital stock, productivity and demand realization, firm i chooses variable inputs $L_{i,t}$ to maximize its instantaneous gross profit

$$\pi_{i,t} = \max_{L_{i,t}}\{P_{i,t}Q_{i,t} - wL_{i,t}\}$$

Optimization yields the maximized value of gross profit

$$\pi_{i,t} = \frac{h_i}{1-\gamma_i}Z_{i,t}^{\gamma_i}\widehat{K}_{i,t}^{1-\gamma_i} \tag{1}$$

where

$$Z_{i,t} = X_{i,t}\left(A_{i,t}\right)^{\varepsilon_i-1}$$
$$\gamma_i = \frac{1}{1+\beta_i(\varepsilon_i-1)} \tag{2}$$

and

$$h_i = (1-\gamma_i)\left(\frac{\gamma_i\varepsilon_i-1}{w}\right)^{\gamma_i\varepsilon_i-1}(\gamma_i\varepsilon_i)^{-\gamma_i\varepsilon_i}$$

Denote sales as $Y_{i,t} \equiv P_{i,t}Q_{i,t}$.[1] The linear homogeneity of the production technology and the isoelastic demand schedule also imply that the maximized gross profit is

[1] We follow the investment literature, such as Abel and Eberly (1999), in using Q to denote the quantity of output, calling the product of price and quantity of output as sales and denoting it as Y. In the produtivity literature, such as Hsieh and Klenow (2009), Y is simply the quantity of output, which is equivalent to the Q in our model.

a constant proportion of sales, .

$$\frac{\pi_{i,t}}{Y_{i,t}} = \frac{1}{\gamma_i \varepsilon_i} = \beta_i (1 - \frac{1}{\varepsilon_i}) + \frac{1}{\varepsilon_i} = \frac{1}{\varepsilon_i}(1 - \beta_i) + \beta_i \tag{3}$$

In Equation (1) we have used $Z_{i,t}$ to incorporate stochastics from both demand $X_{i,t}$ and productivity $A_{i,t}$, which is called 'profitability' in Cooper and Haltiwanger (2006) or 'business condition' in Bloom (2009). The law of motion for $Z_{i,t}$ is given by

$$\begin{aligned} \log Z_{i,t} &= \mu_i t + z_{i,t} \\ z_{i,t} &= \rho z_{i,t-1} + e_{i,t} \end{aligned} \tag{4}$$

where $0 < \rho < 1$, $e_{i,t} \overset{i.i.d.}{\sim} N(0, \sigma^2)$, and $z_{i,0} = 0$. Equation (4) implies a common level of persistence and uncertainty in the stochastic productivity/demand. However, the growth rate of productivity/demand is firm-specific and the productivity/demand shocks are idiosyncratic.

2.2 Distortions and Frictions

In contrast to variable inputs, investment may be subject to both distortions and frictions. Similar to Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), we use τ_i to generically refer to the effect of various policy or institutional distortions on the purchase price of capital of firm i. Therefore the actual capital goods price faced by firm i is

$$P_i^K = (1 + \tau_i)\, P^K$$

For example, a positive value of τ_i corresponds to a firm with no access to finance hence facing an actual capital goods price higher than the competitive price; while an investment tax credit is represented by a negative value of τ_i.

Meanwhile various investment frictions prevent instantaneous and costless adjustment of capital stock. Following Cooper and Haltiwanger (2006) and Bloom (2009), we consider three forms of capital adjustment costs,

$$G(Z_{i,t}, K_{i,t}; I_{i,t}) = \frac{b^q}{2} \left(\frac{I_{i,t}}{K_{i,t}} \right)^2 K_{i,t} - b^i P_i^K I_{i,t} \mathbf{1}_{[I_{i,t}<0]} + b^f \mathbf{1}_{[I_{i,t}\neq 0]} \pi_{i,t}$$

where $\mathbf{1}_{[I_t<0]}$ and $\mathbf{1}_{[I_t \neq 0]}$ are indicators for negative and non-zero investment; b^i can be interpreted as the difference between the purchase price and the sale price expressed as a percentage of the purchase price of capital goods; b^f is interpreted as the fraction of gross profit loss due to any non-zero investment; and b^q measures the magnitude of quadratic adjustment costs.

By paying the cost of purchasing capital and adjusting capital, new investment $I_{i,t}$ contributes to productive capital $\widehat{K}_{i,t}$ immediately in year t, which depreciates at the end of the year.[2] The law of motion for capital is therefore

$$K_{i,t+1} = (1-\delta)\left(K_{i,t} + I_{i,t}\right) \equiv (1-\delta)\widehat{K}_{i,t} \tag{5}$$

where δ is the constant depreciation rate common across firms.

2.3 Investment Decision

Define the net profit of the firm as the gross profit net of quadratic and fixed adjustment costs

$$\Pi(Z_{i,t}, K_{i,t}; I_{i,t}) = \left(1 - b^f \mathbf{1}_{[I_{i,t}\neq 0]}\right)\pi(Z_{i,t}, K_{i,t}; I_{i,t}) - \frac{b^q}{2}\left(\frac{I_{i,t}}{K_{i,t}}\right)^2 K_{i,t}$$

In each period investment is chosen to maximize the discounted present value of dividends, which is the net profit minus investment expenditure. Investors allocate capital until the required rate of return on capital is equalized across different firms. Suppose this required rate of return is r, at which investors discount future dividends, this problem is defined by the stochastic Bellman equation,

$$V(Z_{i,t}, K_{i,t}) = \max_{I_{i,t}} \left\{ \begin{array}{c} \Pi(Z_{i,t}, K_{i,t}; I_{i,t}) - \left(1 - b^i \mathbf{1}_{[I_{i,t}<0]}\right) P_i^K I_{i,t} \\ +\frac{1}{1+r} E_t\left[V(Z_{i,t+1}, K_{i,t+1})\right] \end{array} \right\} \tag{6}$$

together with the law of motion (4) and (5).

It is known that in the presence of adjustment costs, this model in general has no analytical solution. However, using analytical solution in the frictionless case as benchmark provides important predictions on the model properties. If $G(Z_{i,t}, K_{i,t}; I_{i,t}) = 0$, the investment Euler equation is equivalent to the first-order condition in a static investment problem,

$$MRPK_i = U_i$$

The marginal revenue product of capital in this model is proportional to the sales-to-capital ratio, due to the linear homogeneity of sales with respect to productivity/demand and capital stock.

$$MRPK_i = \frac{\partial \pi_{i,t}}{\partial \widehat{K}_{i,t}} = h_i \left(\frac{Z_{i,t}}{\widehat{K}_{i,t}}\right)^{\gamma_i} = \frac{1-\gamma_i}{\gamma_i \varepsilon_i} \frac{Y_{i,t}}{\widehat{K}_{i,t}} \tag{7}$$

The user cost of capital depends on the firm-specific distortion and a common factor J,

$$U_i = (1+\tau_i)\, J$$

where J is known as the Jorgensonian user cost of capital

$$J \equiv P^K \left(\frac{r+\delta}{1+r}\right) \tag{8}$$

[2] Compared with alternative lagged timing assumption, such as $K_{t+1} = (1-\delta)K_t + I_t$, our timing assumption does not affect the qualitative implication of the model, but allows for a closed-form solution to the investment problem in the frictionless case, which does not involve any expectation term. This provides a convenient benchmark for studying the effects of distortions and frictions.

Equivalent to the Equation (2.11) in Hsieh and Klenow (2009), intuitively, the after-distortion marginal revenue product of capital $\frac{MRPK_i}{1+\tau_i}$ is equalized across firms due to capital market competition. The before-distortion marginal revenue product of capital $MRPK_i$ therefore must be higher in firms that face disincentives ($\tau_i > 0$), and be lower in firms that benefit from subsidies ($\tau_i < 0$).

Together with Equation (2), value maximization therefore implies the frictionless log sales-to-capital ratio of firm i is determined by the common Jorgensonian user cost of capital J, the firm-specific distortion τ_i, and the firm-specific capital share β_i and demand elasticity ε_i.

$$\log\left(\frac{Y_{i,t}}{\widehat{K}_{i,t}}\right)^* = \log J + \log\left(1+\tau_i\right) - \log\left[\beta_i\left(1-\frac{1}{\varepsilon_i}\right)\right] \tag{9}$$

It is also straightforward to derive the optimal productive capital stock in the frictionless case,

$$\widehat{K}^*_{i,t} \equiv \left(I_{i,t}+K_{i,t}\right)^* = H_i Z_{i,t} \tag{10}$$

which implies the optimal frictionless investment rate as below

$$\left(\frac{I_{i,t}}{K_{i,t}}\right)^* = H_i\left(\frac{Z_{i,t}}{K_{i,t}}\right) - 1 \tag{11}$$

where

$$H_i = \left(\frac{h_i}{U_i}\right)^{\frac{1}{\gamma_i}}$$

Equation (11) and (10) imply that without any friction, the optimal investment rate is a linear function of productivity/demand relative to inherited capital stock to meet the imbalance between the optimal productive capital stock and the level of productivity/demand in each period, where the slope term H_i reflects production technology β_i, demand elasticity ε_i, the factor price of variable inputs w, and the user cost of capital U_i.

In the presence of adjustment costs, optimal investment policy can be solved out using numerical dynamic programming method. Figures 1.1-1.3 illustrate these policies under different forms of adjustment costs. First, irrespective to the form of adjustment costs, the optimal investment policy is always a non-decreasing function of the marginal revenue product of capital. Second, in the presence of quadratic adjustment costs capital accumulation is through a series of small and continuous adjustment. Finally, the optimal investment policy is a 'barrier control' policy in the presence of irreversibility and a 'jump control' policy in the presence fixed adjustment costs.

Another important property of this investment model is that, despite the presence of adjustment costs, in the long run both capital stock and sales will grow at the same rate as the stochastic productivity/demand (see Bloom, 2000). This is essentially because when a firm is on its balanced growth path, the gap between friction and frictionless capital stock is bounded.

$$\Delta \log Y_{i,T} \equiv \lim_{T\to\infty}\frac{1}{T}\ln\left(Y_{i,T+t}/Y_{i,t}\right) = \lim_{T\to\infty}\frac{1}{T}\ln\left(\widehat{K}_{i,T+t}/\widehat{K}_{i,t}\right) = \mu_i \tag{12}$$

2.4 Losses in Aggregate TFP and Capital Stock

To study the effect of distortions on aggregate TFP loss, consider N firms in the economy each with capital stock $\widehat{K}_i$. Without idiosyncratic distortions, the first-best allocation of capital implies that

$$\widehat{K}_{i,t}^{*} = \frac{Z_{i,t}}{Z_t^{*}}\widehat{K_t}$$

and

$$Y_t^{*} = \frac{\gamma \varepsilon h}{1-\gamma}\left(Z_t^{*}\right)^{\gamma}\widehat{K_t}^{1-\gamma}$$

where $\widehat{K}_t = \sum_{i=1}^{N}\widehat{K}_{i,t}$ is the existing aggregate capital stock of the economy; $Z_t^{*} = \sum_{i=1}^{N} Z_{i,t}$ is the first-best aggregate TFP.[3] Y_t^{*} is the first-best revenue-based aggregate output.

In contrast, distortions in the capital goods prices may lead to capital misallocation and potential loss in aggregate TFP. The actual aggregate output is

$$Y_t = \frac{\gamma \varepsilon h}{1-\gamma}\sum_{i=1}^{N}\left(Z_{i,t}^{\gamma}\widehat{K}_{i,t}^{1-\gamma}\right) = \frac{\gamma \varepsilon h}{1-\gamma}Z_t^{\gamma}\widehat{K}_t^{1-\gamma}$$

in which the actual aggregate TFP is

$$Z_t = \left[\frac{\left(\sum_{i=1}^{N}\frac{Z_{i,t}}{k_{i,t}^{1-\gamma}}\right)}{\left(\sum_{i=1}^{N}\frac{Z_{i,t}}{k_{i,t}}\right)^{1-\gamma}}\right]^{\frac{1}{\gamma}}$$

where the wedge is defined as

$$k_{i,t} \equiv \frac{Z_{i,t}}{\widehat{K}_{i,t}}$$

Therefore the measure of aggregate TFP loss in this model can be calculated as

$$\begin{aligned}
\Delta \log TFP_t &= \log\left(\frac{Z_t}{Z_t^{*}}\right) \\
&= \frac{1}{\gamma}\left[\log\left(\sum_{i=1}^{N}\frac{Z_{i,t}}{k_{i,t}^{1-\gamma}}\right) - (1-\gamma)\log\left(\sum_{i=1}^{N}\frac{Z_{i,t}}{k_{i,t}}\right)\right] - \log\left(\sum_{i=1}^{N} Z_{i,t}\right) \\
&= \frac{1}{\gamma}\left[\log\left(\sum_{i=1}^{N}\left(Z_{i,t}^{\gamma}\widehat{K}_{i,t}^{1-\gamma}\right)\right) - (1-\gamma)\log\left(\sum_{i=1}^{N}\widehat{K}_{i,t}\right) - \gamma\log\left(\sum_{i=1}^{N} Z_{i,t}\right)\right]
\end{aligned}$$

Intuitively, idiosyncratic distortions τ_i generate a dispersion in the user cost of capital hence a dispersion in the wedge $k_{i,t}$. In the absence of distortion the user cost of capital would be common across firms and $k_{i,t}$ would degenerate to a constant $k = \left(\frac{J}{h}\right)^{\frac{1}{\gamma}}$. Thus the actual aggregate TFP Z_t would be the same as the first-best aggregate TFP Z_t^{*}. This implies that the dispersion of $k_{i,t}$ is a direct indicator for

[3] Similar to Foster, Haltiwanger and Syverson (2008), the TFP considered in this paper is revenue-based, or it is the TFPR instead of TFPQ.

the magnitude of aggregate TFP loss. Although $k_{i,t}$ itself is unobservable, Equation (7) links it to log sales-to-capital ratio $\log\left(\frac{Y_{i,t}}{\widehat{K}_{i,t}}\right)$, which is observable. The property that the negative effect of distortions on aggregate TFP can be summarized by the dispersion of log sales-to-capital ratio is similar to that modelled in Hsieh and Klenow (2009) and Midrigan and Xu (2009).

To study the effect of frictions on capital accumulation, we calculate on average how much the actual log capital stock is different from the frictionless log capital stock. Hence the aggregate capital stock loss is measured as

$$\begin{aligned}\Delta \log \widehat{K_t} &= \log\left(\frac{\widehat{K_t}}{\widehat{K}_t^*}\right) \\ &= \log\left(\frac{\sum_{i=1}^{N}\widehat{K}_{i,t}}{\sum_{i=1}^{N}\widehat{K}_{i,t}^*}\right) \\ &= \log\left(\sum_{i=1}^{N}\widehat{K}_{i,t}\right) - \log\left(\sum_{i=1}^{N}\widehat{K}_{i,t}^*\right)\end{aligned}$$

Without a closed-form solution to the investment problem in the presence of adjustment costs, there is no specific conclusion one can draw about how much the actual log capital stock would be lower or higher than the frictionless benchmark. In the case of irreversibility, Abel and Eberly (1999) demonstrate that irreversibility may increase or decrease capital accumulation due to the opposite user cost effect and hangover effect. Furthermore, an increase in uncertainty can either increase or decrease capital stock under irreversibility relative to that under reversibility. In the presence of quadratic adjustment costs, as illustrated in Bond, Söderbom and Wu (2011), capital stock would be unambiguously lower than the frictionless case, since investment in the presence of quadratic adjustment costs incurs a cost in addition to the Jorgensonian user cost of capital. The loss of capital stock is larger under a higher level of uncertainty. Wu (2009) shows that the effect of fixed adjustment costs on capital accumulation is the same as quadratic adjustment costs at complete certainty, but is the same as irreversibility in an uncertain environment.

3 Empirical Specification

3.1 Unobserved Heterogeneities

The goal of this paper is to quantify the effects of distortions and frictions using the above framework. Since the causes of distortions (τ_i) and frictions $\left(b \equiv \left[b^q, b^i, b^f\right]\right)$ are not observable directly, we estimate this investment model in an indirect fashion. The basic strategies are that, first, according to Equation (9) we rely on the distribution of log sales-to-capital ratio $\left(\log\left(\frac{Y_{i,t}}{\widehat{K}_{i,t}}\right)\right)$ to estimate the magnitude of distortions ; and second, according to Figure 1a-1c we use the distribution and dynamics of investment rate $\left(\frac{I_{i,t}}{K_{i,t}}\right)$ to estimate the form and magnitude of adjustment costs.

The key challenge in the first strategy is that both heterogeneities in distortions τ_i and heterogeneities in capital share β_i or demand elasticity ε_i will lead to a dispersion in $\left(\log\left(\frac{Y_{i,t}}{\widehat{K}_{i,t}}\right)\right)$. To distinguish heterogeneities in τ_i from those in β_i or ε_i , we therefore use additional information from profit-to-sales ratio $\left(\frac{\Pi_{i,t}}{Y_{i,t}}\right)$, which depends on β_i and ε_i as show in Equation (3). However, without separate information about quantity of output $(Q_{i,t})$ and price of product $(P_{i,t})$, one cannot further distinguish heterogeneities in β_i from those in ε_i in this model. Hence we assume homogeneity in demand elasticity and heterogeneity in capital share.

Assumption 1 ***Heterogeneity in the distortion of capital goods prices:***

$$\tau_i \overset{i.i.d}{\sim} N\left(0, \sigma_\tau^2\right)$$

That is each firm i has a firm-specific distortion τ_i, where τ_i is drawn independently from an identical normal distribution with mean zero and standard deviation σ_τ.

Assumption 2 ***Heterogeneity in the capital share in production function:***

$$\log \beta_i \overset{i.i.d}{\sim} N\left(\mu_{\log\beta}, \sigma_{\log\beta}^2\right)$$

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 $\sigma_{\log\beta}$.

The key challenge in the second strategy is that the distribution and dynamics of investment rate not only depend on the adjustment costs, but also depend on the stochastic process defined in Equation (4). One concern is that a smooth stochastic process (small σ) with low adjustment costs (small b), or a volatile stochastic process (large σ) with high adjustment costs (large b) could both produce a smooth investment series. To solve this identification issue, we follow Bloom (2009) in using additional information from sales growth rate $(\Delta \log Y_{i,t})$. The rational comes from the fact that log sales is a linear combination of log productivity/demand and log capital stock. Therefore using investment rate and sales growth rate jointly distinguishes the stochastic process and adjustment costs simultaneously. Another concern is that differences across firms in the growth rate (heterogeneity in μ_i), as well as high adjustment costs (large b), can both lead to persistent differences across firms in their investment rate and sales growth rate. To get consistent estimate for the adjustment costs, therefore it is important to allow for potential heterogeneities in the growth rate.

Assumption 3 ***Heterogeneity in the productivity/demand growth rate:***

$$\mu_i \overset{i.i.d}{\sim} N\left(\mu_\mu, \sigma_\mu^2\right)$$

That is each firm i has a firm-specific productivity/demand 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 (τ_i, β_i, μ_i) is different. Hence the dynamic programming problem described in Equation (6) must be solved for each firm i at each value of (τ_i, β_i, μ_i), which is infeasible even for a small sample. Therefore this paper adopts a standard approach used in the literature modelling unobserved heterogeneities, for example, Eckstein and Wolpin (1999), to allow for a finite type of firms.

Assumption 4 ***Finite type of firms:*** *There are* $3 \times 3 \times 3$ *types of firms, each comprising a fixed proportion* $1/(3 \times 3 \times 3)$ *of the population, where the type set is defined as* $\digamma = \{(\tau_u, \beta_v, \mu_x) : u = 1, 2, 3; v = 1, 2, 3; x = 1, 2, 3\}$.

3.2 Measurement Errors

In addition to a rich structure of heterogeneities, another novelty of our empirical specification is that we model and estimate potential measurement errors in key variables. This is motivated by two facts. First, measurement errors are common in firm-level data. The identification strategy discussed above employes four variables: profit-to-sales ratio $(\Pi_{i,t}/Y_{i,t})$; log sales-to-capital ratio $\left(\log\left(Y_{i,t}/\widehat{K}_{i,t}\right)\right)$; investment rate $(I_{i,t}/K_{i,t})$ and sales growth rate in log $(\Delta \log Y_{i,t})$. All these variables in ratio or growth rate are constructed from three variables in level: capital stock $K_{i,t}$, sales $Y_{i,t}$ and profit $\Pi_{i,t}$. So in estimating the model using firm-level data, we allow for measurement errors in $K_{i,t}$, $Y_{i,t}$ and $\Pi_{i,t}$.

Second and more fundamentally, measurement errors may contaminate identification which is crucial for the quantitative effects of distortions and frictions. For the effect of distortions, neglecting measurement errors in $K_{i,t}$ or $Y_{i,t}$ may lead to an overestimation in the heterogeneity in τ_i hence overstates the effect of distortions; neglecting measurement errors in $\Pi_{i,t}$ or $Y_{i,t}$ may overestimate the heterogeneity in β_i and underestimate the heterogeneity τ_i hence understates the effect of distortions. For the effect of frictions, measurement errors in $K_{i,t}$ and $Y_{i,t}$ will make the investment rate and sales growth rate series more dispersed. Neglecting such measurement errors will overestimate the volatility of the stochastic process and adjustment costs, hence overstates the effect of frictions.

Assumption 5 ***Measurement errors in the data:***

$$\begin{aligned} K_{i,t} &= K'_{i,t} \exp(e^K_{i,t}), \; \textit{where } e^K_{i,t} \overset{i.i.d}{\sim} N(0, \sigma^2_{meK}) \\ Y_{i,t} &= Y'_{i,t} \exp(e^Y_{i,t}), \; \textit{where } e^Y_{i,t} \overset{i.i.d}{\sim} N(0, \sigma^2_{meY}) \\ \Pi_{i,t} &= \Pi'_{i,t}(1 + e^Y_{i,t}), \; \textit{where } e^\Pi_{i,t} \overset{i.i.d}{\sim} N(0, \sigma^2_{me\Pi}) \end{aligned}$$

Here $K_{i,t}$, $Y_{i,t}$ and $\Pi_{i,t}$ denote the observed capital stock, sales and profit, $K'_{i,t}$, $Y'_{i,t}$ and $\Pi'_{i,t}$ denotes the true underlying capital stock, sales and profit which are not measured accurately in the data. There is a multiplicative structure for measurement errors in these variables, with mean zero and standard deviation σ_{meK}, σ_{meY} and $\sigma_{me\Pi}$, respectively. The specification for measurement errors in capital stock and sales guarantees positive values of these two variables, while the specification for measurement errors in profit allows for the possibility that recording errors may lead to a loss in the measured profit.

3.3 Data Description

Since the estimation method we adopt is fully structural and parametric, to take into account the effect of potential model misspecification on the estimated effects, we estimate the model for both UK and Chinese firms and use the results of UK as our critical benchmark.

The UK data employed in this paper has been analyzed previously by Bloom, Bond and Van Reenen (2007), for the investment dynamics under uncertainty and irreversibility. These firm-level data are taken from the consolidated accounts of manufacturing firms listed on the U.K. stock market and are obtained from the Datastream on-line service. The cleaned sample we use contains firm-level data for a panel of 629 firms between 1972 and 1991. On average there are 9 annual observations per firm.

The data for Chinese firms are from the Chinese Manufacturing Enterprise Survey. Questionnaires were designed and surveys were implemented by economists at the University of Michigan in collaboration with the Economics Research Institute of the Chinese Academy of Social Sciences. The survey instrument was divided into two parts. The objective part was directed to the firm's chief accountant. It is purely based on accounting information concerning the enterprises. The subjective part was directed to the chief managers–roughly equivalent to the CEOs–of the enterprises personally. It contains attitudinal and qualitative questions with multiple choices. The sample we use for estimation is made of a panel of 701 enterprises between 1994 to 1999. These enterprises were sampled almost evenly from four provinces in China (Jiangsu, Sichuan, Shanxi and Jilin) that together contribute about 20% of China's industrial output. The sample covers 39 industries in total, representative of China's overall industrial structure.

Four key variables are collected from both dataset: investment ($I_{i,t}$), capital stock ($K_{i,t}$), sales ($Y_{i,t}$), and profit ($\Pi_{i,t}$). In the UK sample, investment is defined as total new fixed assets (DS435) less sales of fixed assets (DS423). Capital stock is constructed by applying a perpetual inventory procedure with a depreciation rate of 0.08. The starting value was based on the net book value of the tangible fixed capital assets (DS339) in the first observation within our sample period, adjusted for previous inflation. Subsequent values were obtained using accounts data on investment and asset sales and an aggregate series for investment goods prices. Sales is the value of total sales (DS104) deflated by the aggregate GDP deflator. Profit is recovered by adding depreciation (DS136) back to the operating profit (DS137). Since operating profit is the net profit before interest, tax and after depreciation, this gives us a profit before interest, tax and depreciation.

In the Chinese sample, we use annual gross investment as a measure of investment expenditure (B108). Using annual average net book value of tangible fixed capital assets (B11) and investment expenditure of each year (B108), capital stock is constructed according to Equation (5) with a discount rate of 0.035. Sales is defined as sales revenue of products (B31). Since China has experienced a period from high inflation to deflation during 1994 to 1999, the survey explicitly asked the annual percentage change in the price of its main product for each firm and in each year (B140). We use this information to deflate the sales series. The profit is constructed using the bottom-up method. That is we start with the profit after depreciation, interest and tax (B43), to recover the profit before interest, tax and depreciation by topping up depreciation (B10), interest (B41) and tax (B38).

One potential concern in comparing the UK and Chinese results is that firms in our UK sample are on average larger than those in our Chinese sample. The mean and median number of employees are 4856 and 1102 in UK, and are 2011 and 1055 in China. One possibility is that the firm-level data from UK might be consolidated across several plants within the firm. As pointed out by Bloom (2009), investment rate is featured by spikes and zeros at the plant-level but by much smoother serials at the firm-level. Without accounting for possible aggregation in the firm-level data could thus lead to an overestimation for the quadratic adjustment costs and an underestimation for the non-convex adjustment costs. To make sure the comparability across these two samples, we assume that the UK data are aggregated over two plants and the Chinese data are from a single plant so that plants in UK and in China have similar size in terms of average number of employees.

Assumption 6 ***Aggregation:*** *Each UK firm is aggregated over* 2 *plants. For each plant j of firm i in period t, the law of motion for $Z_{j,i,t}$ is given by*

$$\begin{aligned} \log Z_{j,i,t} &= \mu_i t + z_{j,i,t} \\ z_{j,i,t} &= \rho z_{j,i,t-1} + \frac{1}{\sqrt{2}} e_{i,t} + \frac{1}{\sqrt{2}} e_{j,i,t} \end{aligned}$$

where $e_{i,t} \overset{i.i.d.}{\sim} N(0,\sigma^2)$, $e_{j,i,t} \overset{i.i.d.}{\sim} N(0,\sigma^2)$, $e_{i,t} \perp e_{j,i,t}$, and $e_{1,i,t} \perp e_{2,i,t}$.

That is plants ($j = 1,2$) in the same firm i share the common type (τ_i, β_i, μ_i) and a common firm-level productivity/demand shock $e_{i,t}$, but also have a plant-specific productivity/demand shock $e_{j,i,t}$. The $\frac{1}{\sqrt{2}}$ equal weight of firm-level shock and plant-level shock implies that the overall level of uncertainty is still σ for a firm with two plants, which is comparable to the level of uncertainty from a single-plant firm as in China.

4 Structural Estimation

This section estimates the structural parameters in the model and in the empirical specification using the MSM. Readers who are focused on the simulated effects of distortion and friction may skip to Section 5.

4.1 Method of Simulated Moments

The MSM has been widely employed in the recent empirical investment literature. 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; Henessy and Whited (2007), Schündeln (2006) and Bond, Söderbom and Wu (2007) estimate the cost of financing investment, all through this structural econometric approach. To be more specific, following Gouriéroux and Monfort (1996), the **MSM estimator** Θ^* solves

$$\widehat{\Theta}^* = \arg\min_{\Theta} \left(\widehat{\Phi}^D - \frac{1}{S}\sum_{s=1}^{S} \widehat{\Phi}_s^M(\Theta) \right)' \Omega \left(\widehat{\Phi}^D - \frac{1}{S}\sum_{s=1}^{S} \widehat{\Phi}_s^M(\Theta) \right) \tag{13}$$

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

Suppose the empirical dataset is a panel with N firms and T years. Given the unobserved heterogeneities across firms, the asymptotics is for fixed T and $N \to \infty$. At the efficient choice for the weighting matrix Ω^*, the MSM procedure provides a global specification test of the overidentifying restrictions of the model:

$$\begin{aligned} OI &= \frac{NS}{1+S} \left(\widehat{\Phi}^D - \frac{1}{S}\sum_{s=1}^{S} \widehat{\Phi}_s^M(\Theta) \right)' \Omega^* \left(\widehat{\Phi}^D - \frac{1}{S}\sum_{s=1}^{S} \widehat{\Phi}_s^M(\Theta) \right) \\ &\sim \chi^2 \left[\dim\left(\widehat{\Phi}\right) - \dim(\Theta) \right]. \end{aligned} \tag{14}$$

4.2 Parameters

4.2.1 Parameters to Estimate

Table 1 lists the set of parameters to estimate (Θ). It includes the key parameter characterizing the distortion σ_τ; three parameters measuring the magnitude of each form of capital adjustment costs (b_q, b_i, b_f); the value of demand elasticity ε; mean and standard deviation of the log capital share $\mu_{\log\beta}$ and $\sigma_{\log\beta}$; mean and standard deviation of the growth rate μ_μ and σ_μ; the standard deviation of productivity/demand shocks or the level of uncertainty σ; and the standard deviations of the measurement errors in capital, sales and profit σ_{meK}, σ_{meY}, and $\sigma_{me\Pi}$.

4.2.2 Predetermined Parameters

In addition to these 13 structural parameters, the depreciation rate δ, the discount rate r and the capital goods prices P^K also affect the investment decision through the Jorgensonian user cost of capital J. We pin down the depreciation rate for UK and China by the difference between $mean\left(\log\left(1+\frac{I_{i,t}}{K_{i,t}}\right)\right)$ and $mean\left(\Delta\log Y_{i,t}\right)$,[4] which are 0.08 and 0.035, respectively. As for the discount rate, a necessary condition for finite firm value is that $\exp\left(\mu_i\right) < 1+ r$. The high growth rate of the Chinese firms therefore requires a minimum value of $r = 0.12$. To maintain comparability, we impose $r = 0.12$ for the UK sample as well. A discount rate at 0.12 seems to be high compared with typical value for discount rate imposed in most macro literature. However, from the point of view of firm owners, a required rate of return to capital at 12% is a conservative estimate. Bai, Hsieh and Qian (2005) have found that in China the aggregate rate of return to capital averaged 25% during 1978-1993, fell during 1993-1998, and has become flat at roughly 20% since 1998. Following most investment literature, we normalize the capital goods price to unity so that $\log P^K = 0$ in both UK and China. A later section considers the sensitivity of the estimates to imposing different values for δ, r and $\log P^K$.

To determine the serial correlation in the stochastic productivity/demand, we follow Cooper and Haltiwanger (2006) by estimating the following dynamic panel data model,[5]

$$\log Y_{i,t} = \alpha + \rho\log Y_{i,t-1} + (1-\gamma)\log\widehat{K}_{i,t} - \rho\,(1-\gamma)\log\widehat{K}_{i,t-1} + \eta_i + e_{i,t}$$

We estimate this equation using system GMM and allow for a complete set of year dummies to capture the aggregate shocks. ρ is estimated at 0.873 (with two-step robust standard errors 0.041) for UK and 0.641 (with two-step robust standard errors 0.051) for China. The estimator of ρ for UK is very close to the value 0.885 found in Cooper and Haltiwanger (2006), while a substantially lower estimator for China may reflect the attenuation bias due to measurement errors in the sales data. Therefore we impose $\rho = 0.8732$ for both UK and China in estimating the investment model.

4.3 Moments and Identification

4.3.1 Features of Empirical Moments

Table 2 lists the set of moments to match $\left(\widehat{\Phi}^D\right)$. This includes means, between-group standard deviations, within-group standard deviations, skewness, serial correlations for profit-to-sales ratio $(\Pi_{i,t}/Y_{i,t})$, log sales-to-capital ratio $\left(\log\left(Y_{i,t}/\widehat{K}_{i,t}\right)\right)$, investment rate $(I_{i,t}/K_{i,t})$ and sales growth rate $(\Delta\log Y_{i,t})$; two moments which captures how investment and sales growth rate response to a proxy for the marginal revenue product of capital $(\log(Y_{i,t}/K_{i,t}))$, and two moments that report the proportion of investment spikes $(I_{i,t}/K_{i,t} > 0.2)$ and investment inaction $(I_{i,t}/K_{i,t} = 0)$.

[4] This is because by capital accumulation fomular Equation (5), $\log\left(1+\frac{I_{i,t}}{K_{i,t}}\right) = \log\left(\frac{K_{i,t}+I_{i,t}}{K_{i,t}}\right) = \log\left(\frac{\widehat{K}_{i,t}}{\widehat{K}_{i,t-1}(1-\delta)}\right) = \triangle\log\widehat{K}_{i,t} - \log(1-\delta) \simeq \triangle\log\widehat{K}_{i,t} + \delta$. While according to Equation (12), $\triangle\log\widehat{K}_{i,t} = \triangle\log Y_{i,t} = \mu_i$.

[5] This equation is derived by taking logs on both sides of the sales equation $Y_{i,t} = \frac{\gamma_i\varepsilon_i h_i}{1-\gamma_i} Z_{i,t}^{\gamma_i}\widehat{K}_{i,t}^{1-\gamma_i}$, quasi differencing and replacing $\log Z_{i,t}$ and $\rho\log Z_{i,t-1}$ using the AR(1) structure specified in Equation (4).

The left panel of Table 2 reports the value of these empirical moments and their standard errors estimated from the UK data, while the right panel presents the corresponding values for the Chinese sample. On average firms in China have similar profitability and investment rate as in UK, but a lower log sales-to-capital ratio and a higher sales growth rate, both of which are consistent with a lower depreciation rate imposed in China than in UK. In both countries, the between-group standard deviation for profit-to-sales ratio and log sales-to-capital ratio are much larger than the within-group counterparts, which highlights the importance of unobserved heterogeneities in β_i and/or in τ_i. Although log sales-to-capital ratio is indeed more dispersed in China than in UK, one cannot infer more severe distortion in China simply from this difference, since the profit-to-sales ratio is also more dispersed in China than in UK. Both investment rate and sales growth rate are more volatile in China than in UK, which may imply a higher level of uncertainty or more measurement errors in China. In both samples, profit-to-sales ratio is positively skewed and log sales-to-capital ratio is much more symmetric. This justifies the log-normal assumption for β_i and normality assumption for τ_i. Investment rate is positively skewed and sales growth rate is much more symmetric. This justifies the normality assumption for μ_i and highlights the importance of irreversibility in both samples. The high serial correlation for both profit-to-sales ratio and log sales-to-capital ratio is another indicator for the importance of unobserved heterogeneities in β_i and/or in τ_i. Investment rate is positively correlated in both samples, which is consistent with the presence of quadratic adjustment costs. Sales growth rate is positively correlated in UK but negatively correlated in China. This implies that unobserved heterogeneities in μ_i might be more relevant in the UK sample and measurement errors in sales might be greater in the Chinese sample. The low correlation between investment rate and sales growth rate to the proxy of MRPK is consistent with the importance of capital adjustment costs, but is also consistent with large heterogeneities in the data. Finally, UK has a smaller proportion of investment spikes and investment inaction than China. This may be the result of smaller non-convex adjustment costs, or be the result of more aggregation in UK than in China.

4.3.2 Illustration for Identification

We discuss why this set of moments may identify the parameters of our interest by illustrating how different moments vary with underlying parameters in different panels of Table 3.[6] We start with a model in which there is no capital adjustment costs, unobserved heterogeneities, and measurement errors and label it as Model A in Table 3.1. In this baseline model there is virtually no variation in profit-to-sales ratio and log capital-to-sales ratio. Investment rate and sales growth rate are very volatile, negatively serially correlated and fully response to proxy of MRPK. About 40% firms

[6]In all the simulations reported in Table 3, we impose $r = 0.12$, $\delta = 0.05$, $\mu_{\log \beta} = -2.45$, $\varepsilon = 25$, $\rho = 0.8732$, $\mu_\mu = 0.05$ and $\sigma = 0.35$, simulate $S = 10$ pathes for a panel of 10000 firms and 58 years, and calculate moments and TFP and capital stock losses using data in the last 8 years.

invest more than 20% and no firms stay in inaction. As expected, there is neither aggregate TFP loss nor capital stock loss in a model without distortion and friction.

Keeping other parameters constant, Table 3.1 illustrate the moments when $b^q = 0.5$, $b^i = 0.25$ and $b^f = 0.05$, respectively. Comparison with Model A shows which moments are informative about capital adjustment costs. Overall the presence of these adjustment costs reduces the responses of investment rate and sales growth rate to the proxy of MRPK, and generates some within-group variation in the log sales-to-capital ratio. Both the quadratic adjustment costs and irreversibility substantially reduce the volatility and increase the serial correlation of investment rate and sales growth rate. Both fixed adjustment costs and irreversibility generate a sizable proportion of investment inaction and large positive skewness in investment rate and sales growth rate. Aggregate TFP loss varies from 1.9% to 4.7% due to the presence of adjustment costs, which is of similar magnitude as found in Midrigan and Xu (2009). The actual capital stock is lower than the frictionless benchmark in the presence of quadratic and fixed adjustment costs, but higher than the frictionless level with irreversibility, which are both consistent with the prediction of the investment literature. We then simulate a model when all three forms of adjustment costs are in present and call it Model B.

Table 3.2 illustrates the moments when $\sigma_\tau = 0.5$, $\sigma_{\log\beta} = 0.5$ and $\sigma_\mu = 0.025$, imposing zero and positive capital adjustment costs, respectively. Therefore moments in the left and right panels should be compared with Model A and Model B, respectively. Such comparison shows which moments are informative about unobserved heterogeneities. From columns (1) and (2), we find that heterogeneities in τ and β both generate large between-group standard deviation and high serial correlation in log sales-to-capital ratio, but only heterogeneities in β affect profit-to-sales ratio. Although similar dispersion in log sales-to-capital ratio can be generated from either τ and β, only heterogeneity in τ cause a substantial loss in aggregate TFP. Even in a model without any friction, the responsiveness of investment rate and sales growth rate to the proxy of MRPK is much dampened due to the large heterogeneities in the MRPK. The presence of heterogeneities in μ increases the serial correlation in investment rate and sales growth rate, which works in the same direction as quadratic adjustment costs and irreversibility, but also increases the standard deviation of investment rate and sales growth rate, which works in the opposite direction of quadratic adjustment costs and irreversibility. In the last column of Table 3.2, we then simulate a model with both adjustment costs and unobserved heterogeneities and label it as Model C.

Using Model C as benchmark, Table 3.3 illustrates which moments are informative about measurement errors by simulating $\sigma_{meK} = 0.2$, $\sigma_{meY} = 0.2$ and $\sigma_{me\Pi} = 0.2$, respectively. The common finding is that whenever a variable is contaminated with measurement errors, there will be an increase in its within-group standard deviation and a decrease in its serial correlation. In addition, measurement errors in capital stock increase the correlation between investment rate and MRPK, but reduces the correlation between sales growth rate and MRPK. Measurement errors in sales has the opposite effects. Finally, we notice that although measurement errors in capital and sales increases the standard deviation of log capital-to-sales ratio, it will not generate any loss in aggregate TFP.

4.4 Empirical Results

Table 4 presents our estimation results. For each country, the first column reports the optimal estimates of the structural parameters and the second column lists the corresponding numerical standard errors. Simulated moments at these optimal estimates are listed in the lower panel of Table 4 to compare with their empirical counterparts. Overall the model has provided a close fit to the large set of the moments characterizing the distribution and dynamics of four key variables, with an OI value equal to 908 for UK and 825 for China.

In both UK and China, σ_τ is estimated to be significantly different from zero, and is significantly larger in China than in UK. This implies that distortions in capital goods prices exist in both countries, but are indeed greater in China than in UK.

The estimates for two out of three forms of capital adjustment costs are found to be quantitatively important. In particular, $\widehat{b_q} = 0.245$ in UK and $\widehat{b_q} = 0.396$ in China. These quadratic adjustment costs imply an investment friction, which increases the user cost of capital by about 3.1% and 4.9% for UK and China respectively.[7] Similar level of irreversibility is estimated for both countries, which implies that the resale price of capital is about 10% lower than the purchase price of capital.

The estimate for the demand elasticity ε is around 25, which seems to be higher than what the macro literature would typically impose. This is because our model is matching the average level of net profit to sales ratio, which is only around 11% in our samples. Had we matched the gross profit to sales ratio, which is typically beyond 20%, the estimated value for ε does substantially reduce. We report this robustness test in next subsection. The estimated mean and standard deviation for $\log \beta$ implies that capital share β varies from 0.047 to 0.167 with a median at 0.089 in UK, and varies from 0.036 to 0.208 with a median at 0.086 in China. Both the dispersion and median value of our estimate for β are very close to those in Jorgenson, Gollop and Fraumeni (1987). Among the 28 U.S. manufacturing industries they estimated by production function regression over intermediate input, capital input and labor input, the capital share estimate varies from 0.0486 (apparel and other fabricated textile products) to 0.333 (tobacco) with median at 0.098 (electric machinery and equipment supplies). Such estimate for β should be distinguished from the one in an aggregate production function for value added with capital and labor inputs only, where Jorgenson, Gollop and Fraumeni (1987) find a capital share of 0.385 for the U.S. in such an aggregate

[7] In the presence of quadratic adjustment costs only, the first-order condition of optimal investment implies that $K_t = \left[\frac{h}{P^K(J+C_t)}\right]^{\frac{1}{\gamma}}$, where $C_t = b^q\left(\frac{I_t}{K_t}\right) - b^q\left(\frac{1-\delta}{1+r}\right)E_t\left(\frac{I_{t+1}}{K_{t+1}}\right) - \frac{b^q}{2}\left(\frac{1-\delta}{1+r}\right)E_t\left(\frac{I_{t+1}}{K_{t+1}}\right)^2$. If we neglect higher order terms and assume $E_t\left(\frac{I_{t+1}}{K_{t+1}}\right) = \frac{I_t}{K_t}$, C_t can be approximated as $C_t \simeq Jb^q\left(\frac{I_t}{K_t}\right)$. Therefore the quadratic adjustment costs incur an additional cost in the user cost of capital by $b^q\left(\frac{I_t}{K_t}\right)$.

model. Together, our estimate for ε and β implies that at the median level the capital coefficient in the sales/profit function is $1-\widehat{\gamma}=0.680$ in UK and 0.674 in China. Such estimates are within the range of estimates of the revenue returns to scale, varying from 0.82 in Bachman, Caballero and Engel (2006), to 0.592 in Cooper and Haltiwanger (2006).

The estimates for the mean of growth rate is 0.033 and 0.062 for UK and China, respectively, where heterogeneities in growth rate are larger and more significant in UK than in China. The standard deviation for shocks σ is estimated be 0.319 in UK and 0.415 in China. These estimates indicate that on average the productivity/demand grows faster in China than in UK, within UK the productivity/demand is more dispersed across firms, and firms in China face a higher level of uncertainty.

The model estimates significant measurement errors in capital and profit for both UK and China, and in sales for China. For all three variables we consider, the measurement errors are greater in China than in UK.

4.5 Specification Tests

Table 5 reports specification tests for several restricted models for China, where the preferred full model is listed as benchmark. Similar patterns are found for UK.

Columns (1), (2) and (3) show the results of imposing no capital adjustment costs, no unobserved heterogeneities and no measurement errors, respectively. Compared with the preferred full model, the OI value increases a lot for all three models. In particular, a model without capital adjustment costs underestimates magnitude of distortion and level of uncertainty. It generates too little within-group standard deviation for profit-to-sales ratio and log sales-to-capital ratio, but too much within-group standard deviation in investment rate and sales growth rate. It also fails to match the large positive skewness and serial correlation in the investment rate. A model without any unobserved heterogeneities cannot match the large between-group standard deviation in profit-to-sales ratio and log sales-to-capital ratio and tends to overestimate capital adjustment costs and level of uncertainty. A model without measurement errors generates too little within-group standard deviation but too much serial correlation for all the variables. It tends to overestimate distortions, capital adjustment costs and level of uncertainty.

Columns (4), (5) and (6) illustrate the estimates for restricted models without quadratic adjustment costs, without irreversibility, and without irreversibility and fixed adjustment costs, respectively. All these models fit the data worse than the full model, where a combination of quadratic adjustment costs and irreversibility fits the data best. This is similar to the finding in Bloom (2009) for the firm-level data. A combination of quadratic and fixed adjustment costs can also fit the model reasonably well, which is consistent with Cooper and Haltiwanger (2006). However, among the three forms of adjustment costs, quadratic adjustment costs is the most relevant according to the overall fit. This comes to the same conclusion as Eberly, Rebelo and Vincent (2008) for firm-level data.

Columns (7), (8) and (9) present the results for restricted models without heterogeneities in τ, β, and μ, respectively. Comparison between column (7) and the benchmark model tests the null hypothesis $H_o : \sigma_\tau = 0$, which is firmly rejected by the differences in the OI values. This implies that the feature of the data is consistent with the existence of idiosyncratic distortions. Comparison between column (8) and the benchmark model highlights the importance of allowing for heterogeneity in the capital share. A model imposing common capital share would not be able to match the large between-group standard deviation in profit-to-sales ratio. In order to match the large between-group standard deviation in log sales-to-capital ratio, the model will substantially over-estimate the magnitude of distortions. Finally, a model with homogeneous growth rate tends to slightly over-estimate distortion and quadratic adjustment costs.

4.6 Robustness Tests

Table 6 presents results for four robustness tests for China. The benchmark model has imposed $\delta = 0.035$, $r = 0.12$ and $\log P^K = 0$. Column (1), (2) and (3) show the results for the same model but imposing $\delta = 0.045$, $r = 0.15$ and $\log P^K = 0.1$, respectively. All these alternative values imply a higher Jorgensonian user cost of capital. Comparison with the benchmark, we find a higher Jorgensonian user cost of capital indeed leads to a higher log sales-to-capital ratio and fits this empirical moment better. Nevertheless, the estimates for other parameters, in particular, for distortions and capital adjustment costs, are relatively robust to the choices of these three parameters. Therefore the key finding of our estimation for significant distortions and frictions does not depend on our choice of Jorgensonian user cost of capital.

Column (4) re-estimates the model for China using gross profit to replace the net profit in the set of the moments. Gross profit is the difference between sales revenue and the costs of goods sold. Subtracting selling, general and administrative expenses from gross profit leads to net profit, or profit before interest, tax and depreciation. Since there is no information about gross profit in UK, we have used the net profit for both UK and China for comparison. With information about both gross and net profit for China, we estimate the model to see whether our result depends on the choice of profit. As we see in the Column (4), overall the model fits the data better using gross profit and the estimated demand elasticity reduces from 25 to 15.5. However, the estimates for distortions and frictions are not significantly different from our benchmark model, where net profit has been employed.

4.7 Potential Heterogeneities in δ

One caveat of our empirical strategy is to attribute all the heterogeneities in the user cost of capital to idiosyncratic distortions in capital goods prices and assume common depreciation rate. At the other extreme, one could attribute all the heterogeneities in the user cost of capital to firm-specific depreciation rate and assume common capital goods price across firms.

To check to what extent the heterogeneities in the user cost of capital may be explained by firm-specific depreciation rate (δ_i), we compare the between-group standard deviation of log investment rate $\left(\log\left(1+\frac{I_{i,t}}{K_{i,t}}\right)\simeq\mu_i+\delta_i\right)$ and sales growth rate ($\Delta\log Y_{i,t}=\mu_i$), where the difference can be attributed to potential heterogeneities in δ_i. However, such deviations are 0.074 and 0.083 in UK, and 0.099 and 0.106 in China, which reject the possibility of large heterogeneities in δ_i.

5 Quantitative Effects of Distortions and Frictions

5.1 Counterfactual Simulations

The estimated structural model provides a useful framework to quantify the effects of distortions on aggregate TFP and the effects of frictions on capital stock. Table 7.1 and 7.2 simulate these effects for UK and China, respectively. Since there are heterogeneities in both capital share and growth rate, these effects are simulated for different type of firms. In UK, on average the actual aggregate TFP is 30% lower than the first-best aggregate TFP. And the capital stock is 11.2% lower than the frictionless capital stock. Given the log TFP and log capital count for 0.33 and 0.67 in log output, aggregate output is 17.4% lower than the level if there was no such distortions nor frictions.

All else being equal, both the losses in aggregate TFP and in capital increase with the capital share. The losses in capital stock also increase with the growth rate. In other words, firms with larger capital share and higher growth rate suffer most from distortion and friction in investment.

Table 7.2 shows that similar qualitative patterns are found in China. However, quantitatively, the aggregate TFP loss is about 53%, and the capital stock is 21.5% lower than the frictionless level. Both of these effects are substantially larger than those in UK. Together China's aggregate output is 32.3% lower than the distortionless and frictionless level.

We can also apply the estimated structural model as a laboratory, where controlled experiments can be conducted to investigate the hypothetical questions, such as, how aggregate TFP and capital stock losses would differ, if firms in China face distortions and frictions to the extent as in UK? Table 7.3 thus simulates the effects of distortions and frictions for China by imposing its σ_τ, b^q, and b^i to be the corresponding values estimated from UK. Table 7.4 reports gains from the improvement by comparing the quantitative effects in Table 7.2 with those in Table 7.3. We find that averaging across different type of firms, the aggregate TFP in China would enhance by 20.1%, and the capital stock in China would increase by 5.3%, if these Chinese firms had been operating in an environment such as UK. A reduction in distortions and frictions would therefore generate a 6.9% ($=0.344\times 20.1\%$) and a 3.5% ($=0.656\times 5.3\%$) increase in aggregate output, which count for two-thirds and one-third in the overall increase in aggregate output.

5.2 Relating to Observables

The counterfactual simulations indicate that the main reason for more aggregate output loss in China compared to UK is due to the idiosyncratic distortions in the capital goods prices. Since the distortions we model are unobservable, it is interesting to link it with some observable firm characteristics and check whether our model predictions are consistent with common institutional knowledge.

Our starting point is that if there is indeed idiosyncratic distortions in capital goods prices, all else being equal, the log sales-to-capital ratio is higher for a firm facing unfavorable distortions and lower for a firm benefiting from favorable distortions. However, all else is not equal. This is because, first, heterogeneities in capital share and presence of capital adjustment costs may affect the dispersion in log sales-to-capital ratio as well, and second, measurement errors will also increase the dispersion in log sales-to-capital ratio. Our specification tests reported in Table 5 indicate that both of these concerns are relevant in the data. However, as we have illustrated in Table 3, the heterogeneities in capital share can be captured by dispersion in profit-to-sales ratio; the effects of capital adjustment costs can be captured by investment rate dynamics; and finally, measurement errors mainly cause an increase in within-group rather than between-group dispersion. Therefore we focus on the between-group mean of log sales-to-capital ratio $\left\{E_t\left[\log\left(Y_{i,t}/\widehat{K}_{i,t}\right)\right]\right\}_i$ to filter the effects of measurement errors, use between-group mean of profit-to-sales ratio $\{E_t\left[\pi_{i,t}/Y_{i,t}\right]\}_i$ to control heterogeneity in capital share, and include investment rate $\{E_t\left[I_{i,t}/K_{i,t}\right]\}_i$ to control capital adjustment costs. We then test whether the differences in the remaining part of log sales-to-capital ratio across firms are statistically related with some firm characteristics.

Table 8 presents the results of such regression for our Chinese sample. Variables in upper case are dummy variables which indicate firm size, ownership, location and whether the chief manager of the firm is a member of the communist party. The baseline group is a large, collective-owned firm in Jilin province whose chief manager is a member of the communist party. We also include the age of the firm, the age, education and experience of the chief manager to control potential ability bias.

According to Table 8, all else being equal, a small firm faces an actual capital goods price that is 14.6% higher than a large firm. Collective-owned firms face the lowest capital goods prices, while the private owned firms face the highest prices, which is about 65.3% higher than their collective counterpart. The capital goods prices for state-owned firms, firms under share-holding system and foreign-owned firms are somewhere in between. Compared with firms in Jilin province, on average firms in Jiangsu province have a capital goods price that is 36.8% higher. Finally, a firm with a chief manager who is a member of the communist party pays a capital goods price that is 14.9% lower than otherwise.

All else being equal, if one takes the dispersion in the log sales-to-capital ratio as an indicator of idiosyncratic policy and institutional distortions, our exercises imply that small, private-owned firms without political connection in east China face unfavorable distortions compared with large, collective-owned firms with political connection in north-east China, and the magnitude of such distortions is substantial. This finding is consistent with a large literature that links the factor market distortions with various policy and institutional settings in China, such as, Dollar and Wei (2007), Li, Meng, Wang and Zhou (2008) and Brandt, Tombe and Zhu (2010).

6 Conclusion

This paper offers estimates for the effects of distortions and frictions on aggregate TFP loss and capital stock loss in UK and China. We estimate a neoclassical investment model with idiosyncratic distortions in capital goods prices and different forms of capital adjustment costs, by matching profit-to-sales ratio, log sales-to-capital ratio, investment rate and sales growth rate in their distribution and dynamics. Our empirical specification has allowed for potential heterogeneities in other dimensions and measurement errors in the data, which are crucial for consistent estimate for the effects of our interest. Counterfactual simulations indicate that on average reducing the dispersion of capital goods prices to the UK level would enhance aggregate TFP by 20.1% and aggregate output by 6.9% in China, and moving the capital adjustment costs to the UK level would increase capital stock by 5.3% and aggregate output by 3.5% in China. Under this framework, we find that small, private-owned firms in east China without political connection face unfavorable distortions in capital goods prices.

Like most empirical research in this line, the investment model estimated in this paper is first, explicitly partial equilibrium in nature hence omits the market-clearing relative prices, and second, for existing firms only hence neglects entry and exit. Intuitively, taking into account effects from these two aspects may even enlarge the magnitudes estimated in this paper, if one assumes relatively higher capital goods price in China than in UK, and deferred entry and exit due to idiosyncratic capital goods prices. Such extension is beyond the scope of this paper and it is important to develop future works along these two margins.

References

[1] Abel, Andrew B. and Eberly, Janice C. (1999), "The Effects of Irreversibility and Uncertainty on Capital Accumulation", *Journal of Monetary Economics*, 44, 339-377.

[2] Bai, Chong-En, Hsieh, Chang-Tai and Qian, Yingyi (2006), "The Returns to Capital in China", *Brookings Papers on Economic Activity*, 37, 61-102.

[3] Banerjee, Abhijit V. and Duflo, Esther (2005), "Growth Theory through the Lens of Development Economics", in: Philippe Aghion & Steven Durlauf (ed.), *Handbook of Economic Growth*, edition 1, volume 1, chapter 7, 473-552.

[4] Barro, Robert and Sala-I-Martin, X., *Economic Growth*, 1995, McGraw-Hill, New York.

[5] Bloom, Nick (2000), "The Dynamic Effects of Real Options and Irreversibility on Investment and Labour Demand", Institute for Fiscal Studies Working Paper No.W00/15.

[6] Bloom, Nick (2009), "The Impact of Uncertainty Shocks", *Econometrica*, 77, 623-685.

[7] Bloom, Nick, Bond, Stephen R. and Van Reenen, John (2007), "Uncertainty and Investment Dynamics", *Review of Economic Studies*, 74, 391-415.

[8] Bond, Stephen R., Söderbom, Måns and Wu, Guiying Laura (2007), "Investment and Financial Constraints: Empirical Evidence for Firms in Brazil and China", Mimeo, Department of Economics, University of Oxford.

[9] Bond, Stephen R., Söderbom, Måns and Wu, Guiying Laura (2008), "A Structural Estimation for the Effects of Uncertainty on Capital Accumulation with Heterogeneous Firms", Mimeo, Department of Economics, University of Oxford.

[10] Bond, Stephen R., Söderbom, Måns and Wu, Guiying Laura (2011), "Pursuing the wrong options? Adjustment costs and the relationship between uncertainty and capital accumulation", forthcoming, *Economics Letters*.

[11] Brandt, Loren, Tombe, Trevor and Zhu, Xiaodong (2010), "Factor Market Distortions Across Time, Space and Sectors in China", Working Papers, University of Toronto.

[12] Cooper, Russell W. and Ejarque, Joao (2003), "Financial Frictions and Investment: A Requiem in Q", *Review of Economic Dynamics*, 6, 710-728.

[13] Cooper, Russell W. and Haltiwanger, John (2006), "On the Nature of Capital Adjustment Costs", *Review of Economic Studies*, 73, 611-634.

[14] Dollar, David and Wei, Shang-jin (2007), "Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China", NBER Working Paper, No. 13103.

[15] EBERLY, Janice C., REBELO, Sergio. and VINCENT, Nicolas (2008), "Investment and Value: A Neoclassical Benchmark", NBER Working Paper, No. 13866.

[16] ECKSTEIN, Zvi and WOLPIN, Kenneth I. (1999), "Why Youths Drop Out of High School: The Impact of Preferences, Opportunities, and Abilities", *Econometrica*, 67, 1295-1339.

[17] FOSTER, Lucia, HALTIWANGER, John, and SYVERSON, Chad (2008), "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98, 394-425.

[18] JORGENSON, Dale W., GOLLOP, Frank M. and FRAUMENI, Barbara M. (1987), *Productivity and U.S Economic Growth*, toExcel Press.

[19] GOURIÉROUX, Christian and MONFORT, Alain (1996), *Simulation-Based Econometric Methods*, Oxford University Press.

[20] LI, Hongbin, MENG, Lingsheng, WANG, Qian, ZHOU, Li-An (2008), "Political connections, financing and firm performance: Evidence from Chinese private firms", *Journal of Development Economics*, 87, 283-299.

[21] KHAN, Aubhik and THOMAS, Julia K. (2006), "Adjustment Costs", *The New Palgrave Dictionary of Economics*, Palgrave Macmillan.

[22] MANKIW, N.G., ROMER, David and WEIL, D.N. (1992), "A Contribution to the Empiricals of Growth", *Quarterly Journal of Economics*, 107, 407-437.

[23] MIDRIGAN, Virgiliu and XU, Daniel Yi (2009), "Accounting for Plant-Level Misallocation", Working Paper, New York University.

[24] SONG, Zheng Michael, STORESLETTEN, Kjetil and ZILIBOTTI, Fabrizio (2010), "Growing Like China", *American Economic Review*, forthcoming.

[25] RESTUCCIA, Diego, and ROGERSON, Richard (2008), "Policy Distortions and Aggregate Productivity with Heterogeneous Plants", *Review of Economic Dynamics*, 11, 707-720.

[26] WORLD BANK (2005), *A Better Investment Climate for Everyone*, World Development Report, the World Bank and Oxford University Press.

[27] WU, Guiying Laura (2009), *Uncertainty, Investment and Capital Accumulation: A Structural Econometric Approach*, D.Phil. Thesis, University of Oxford.

Figure 1.1: Investment Policy for Quadratic Adjustment Costs

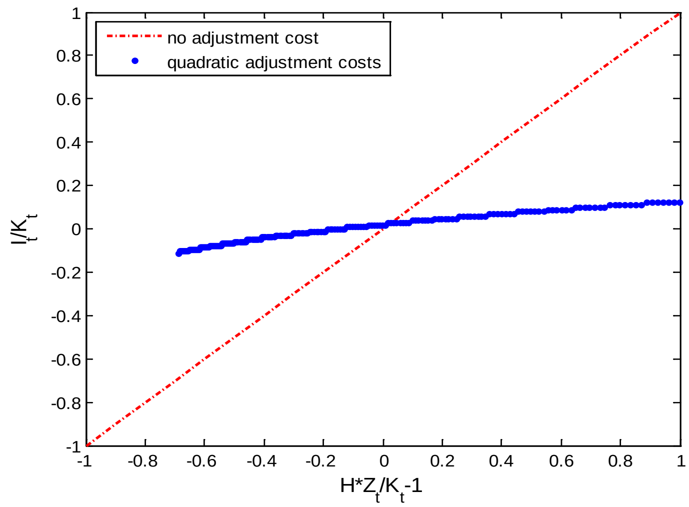

Figure 1.2: Investment Policy for Irreversibility

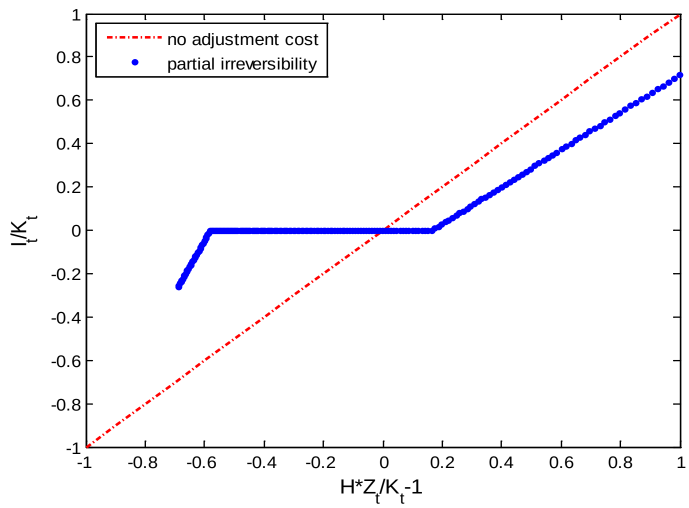

Figure 1.3: Investment Policy for Fixed Adjustment Costs

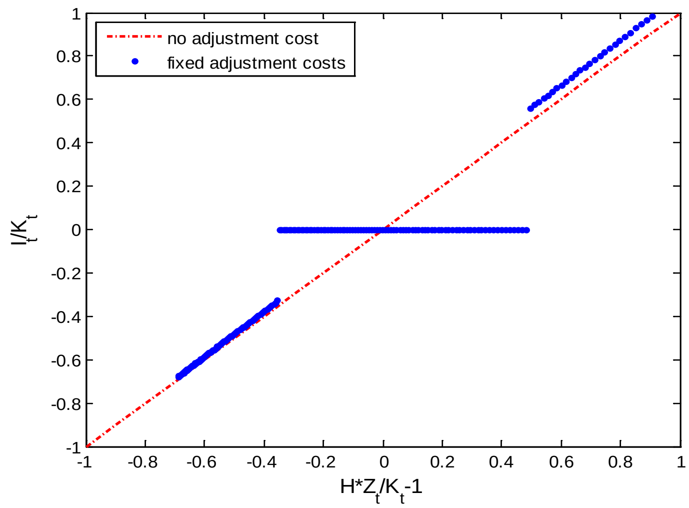

Table 1. Parameters to Estimate

Parameters	Definition
σ_{τ}	standard deviation of heterogeneities in distortion
b^{q}	quadratic adjustment costs
b^{i}	irreversibility
b^{f}	fixed adjustment costs
ε	demand elasticity
$\mu_{log\beta}$	mean of log capital share in production function
$\sigma_{log\beta}$	standard deviation of heterogeneities in log capital share
μ_{μ}	mean of productivity/demand growth rate
σ_{μ}	standard deviation of productivity/demand growth rate
σ	standard deviation of of productivity/demand shocks
σ_{meK}	standard deviation of measurement errors in capital stock
σ_{meY}	standard deviation of measurement errors in sales
$\sigma_{me\Pi}$	standard deviation of measurement errors in profit

Table 2. Empirical Moments for UK and China

	UK		China	
Number of Firms	629		701	
Number of Years	9		6	
Median No. of Employees	1102		1055	
Mean No. of Employees	4856		2011	
Set of Moments	**moments**	**s.e.**	**moments**	**s.e.**
mean(Π/Y)	0.110	0.003	0.111	0.003
mean(log(Y/Khat))	0.749	0.022	0.565	0.027
mean(I/K)	0.125	0.003	0.123	0.004
mean(ΔlogY)	0.031	0.003	0.072	0.004
bsd(Π/Y)	0.049	0.003	0.079	0.002
wsd(Π/Y)	0.028	0.001	0.052	0.001
bsd(log(Y/K))	0.541	0.017	0.777	0.015
wsd(log(Y/K))	0.214	0.005	0.349	0.007
bsd(I/K)	0.095	0.004	0.128	0.006
wsd(I/K)	0.103	0.003	0.109	0.004
bsd(ΔlogY)	0.083	0.004	0.106	0.003
wsd(ΔlogY)	0.143	0.003	0.253	0.004
skew(Π/Y)	0.801	0.065	0.690	0.075
skew(log(Y/Khat))	0.007	0.137	-0.089	0.054
skew(I/K)	2.723	0.096	2.552	0.097
skew(dlogY)	0.837	0.137	-0.045	0.041
scorr(Π/Y)	0.880	0.008	0.716	0.016
scorr(log(Y/Khat))	0.943	0.005	0.899	0.007
scorr(I/K)	0.392	0.023	0.475	0.031
scorr(ΔlogY)	0.222	0.018	-0.285	0.019
corr(I/K, log(Y/K))	0.139	0.022	0.222	0.023
corr(ΔlogY, log(Y/K))	0.151	0.016	0.153	0.015
Prop(I/K>0.2)	0.153	0.007	0.177	0.009
Prop(I/K=0)	0.027	0.003	0.101	0.007

Table 3.1. Illustration for Idenfication of Capital Adjustment Costs

Parameters	**Model A**	**col (1)**	**col(2)**	**col (3)**	**Model B**
	$\boldsymbol{b^q = 0}$	$b^q = 0.5$	$b^q = 0$	$b^q = 0$	$b^q = 0.5$
	$\boldsymbol{b^i = 0}$	$b^i = 0$	$b^i = 0.25$	$b^i = 0$	$b^i = 0.25$
	$\boldsymbol{b^f = 0}$	$b^f = 0$	$b^f = 0$	$b^f = 0.05$	$b^f = 0.05$
Set of Moments					
mean(Π/Y)	**0.123**	0.121	0.123	0.121	0.117
mean(log(Y/Khat))	**0.605**	0.622	0.574	0.619	0.681
mean(I/K)	**0.179**	0.110	0.125	0.176	0.114
mean(ΔlogY)	**0.050**	0.050	0.050	0.050	0.050
bsd(Π/Y)	**0.000**	0.001	0.000	0.001	0.003
wsd(Π/Y)	**0.000**	0.002	0.000	0.003	0.005
bsd(log(Y/K))	**0.001**	0.081	0.071	0.039	0.076
wsd(log(Y/K))	**0.002**	0.094	0.083	0.072	0.089
bsd(I/K)	**0.123**	0.055	0.090	0.139	0.064
wsd(I/K)	**0.416**	0.074	0.216	0.468	0.114
bsd(ΔlogY)	**0.109**	0.067	0.081	0.102	0.072
wsd(ΔlogY)	**0.339**	0.144	0.196	0.290	0.161
skew(Π/Y)	**0.000**	-1.521	0.000	-1.039	-0.304
skew(log(Y/Khat))	**0.000**	-0.019	-1.328	-0.168	-0.561
skew(I/K)	**1.175**	0.304	2.723	2.508	0.542
skew(dlogY)	**0.004**	0.023	1.167	0.855	0.267
scorr(Π/Y)	**N.A.**	0.571	N.A.	-0.062	0.394
scorr(log(Y/Khat))	**N.A.**	0.675	0.666	0.350	0.665
scorr(I/K)	**-0.067**	0.628	0.141	-0.075	0.392
scorr(ΔlogY)	**-0.071**	0.115	0.067	-0.008	0.110
corr(I/K, log(Y/K))	**1.000**	0.973	0.896	0.927	0.924
corr(ΔlogY, log(Y/K))	**1.000**	0.793	0.896	0.972	0.837
Prop(I/K>0.2)	**0.410**	0.166	0.217	0.183	0.372
Prop(I/K=0)	**0.000**	0.001	0.539	0.731	0.496
Loss in TFP and Capital Stock					
ΔlogTFP	**0.000**	-0.047	-0.032	-0.019	-0.040
ΔlogKhat	**0.000**	-0.164	0.092	-0.046	-0.237

Table 3.2. Illustration for Idenfication of Unobserved Heterogeneities

Parameters	**Model A**	col (1)	col(2)	col (3)	**Model B**	col (1)	col(2)	col (3)	Model C
	$\boldsymbol{\sigma_{\log\beta} = 0}$	$\sigma_{\log\beta} = 0.5$	$\sigma_{\log\beta} = 0$	$\sigma_{\log\beta} = 0$	$\boldsymbol{\sigma_{\log\beta} = 0}$	$\sigma_{\log\beta} = 0.5$	$\sigma_{\log\beta} = 0$	$\sigma_{\log\beta} = 0$	$\sigma_{\log\beta} = 0.5$
	$\boldsymbol{\sigma_{\tau} = 0}$	$\sigma_{\tau} = 0$	$\sigma_{\tau} = 0.5$	$\sigma_{\tau} = 0$	$\boldsymbol{\sigma_{\tau} = 0}$	$\sigma_{\tau} = 0$	$\sigma_{\tau} = 0.5$	$\sigma_{\tau} = 0$	$\sigma_{\tau} = 0.5$
	$\boldsymbol{\sigma_{\mu} = 0}$	$\sigma_{\mu} = 0$	$\sigma_{\mu} = 0$	$\sigma_{\mu} = 0.025$	$\boldsymbol{\sigma_{\mu} = 0}$	$\sigma_{\mu} = 0$	$\sigma_{\mu} = 0$	$\sigma_{\mu} = 0.025$	$\sigma_{\mu} = 0.025$
Set of Moments									
mean(Π/Y)	**0.123**	0.135	0.123	0.123	**0.117**	0.128	0.117	0.117	0.128
mean(log(Y/Khat))	**0.605**	0.605	0.605	0.605	**0.681**	0.681	0.685	0.679	0.682
mean(I/K)	**0.179**	0.179	0.179	0.179	**0.114**	0.114	0.114	0.114	0.114
mean(ΔlogY)	**0.050**	0.050	0.050	0.050	**0.050**	0.050	0.050	0.050	0.050
bsd(Π/Y)	**0.000**	0.048	0.000	0.000	**0.003**	0.046	0.003	0.003	0.046
wsd(Π/Y)	**0.000**	0.000	0.000	0.000	**0.005**	0.006	0.005	0.005	0.006
bsd(log(Y/K))	**0.001**	0.521	0.499	0.001	**0.076**	0.520	0.478	0.079	0.703
wsd(log(Y/K))	**0.002**	0.002	0.002	0.002	**0.089**	0.096	0.090	0.090	0.097
bsd(I/K)	**0.123**	0.123	0.123	0.126	**0.064**	0.064	0.064	0.069	0.070
wsd(I/K)	**0.416**	0.416	0.416	0.417	**0.114**	0.116	0.117	0.112	0.117
bsd(ΔlogY)	**0.109**	0.109	0.109	0.112	**0.072**	0.072	0.071	0.075	0.075
wsd(ΔlogY)	**0.339**	0.339	0.339	0.339	**0.161**	0.166	0.161	0.160	0.166
skew(Π/Y)	**0.000**	0.683	0.000	0.000	**-0.304**	0.710	-0.293	-0.332	0.712
skew(log(Y/Khat))	**0.000**	0.000	0.000	-1.300	**-0.561**	0.083	-0.011	-0.577	0.031
skew(I/K)	**1.175**	1.176	1.175	1.178	**0.542**	0.602	0.734	0.562	0.807
skew(dlogY)	**0.004**	0.004	0.004	0.003	**0.267**	0.256	0.308	0.273	0.298
scorr(Π/Y)	**N.A.**	1.000	1.000	1.000	**0.394**	0.986	0.427	0.424	0.987
scorr(log(Y/Khat))	**N.A.**	1.000	1.000	0.252	**0.665**	0.981	0.980	0.676	0.989
scorr(I/K)	**-0.067**	-0.067	-0.067	-0.062	**0.392**	0.377	0.363	0.419	0.379
scorr(ΔlogY)	**-0.071**	-0.071	-0.071	-0.066	**0.110**	0.092	0.104	0.124	0.102
corr(I/K, log(Y/K))	**1.000**	0.546	0.563	0.968	**0.924**	0.368	0.395	0.916	0.291
corr(ΔlogY, log(Y/K))	**1.000**	0.565	0.581	1.000	**0.837**	0.324	0.346	0.832	0.250
Prop(I/K>0.2)	**0.410**	0.410	0.410	0.411	**0.372**	0.363	0.310	0.370	0.308
Prop(I/K=0)	**0.000**	0.000	0.000	0.000	**0.496**	0.497	0.488	0.500	0.495
Loss in TFP and Capital Stock									
ΔlogTFP	**0.000**	0.000	-0.485	0.000	**-0.040**	-0.040	-0.490	-0.040	-0.490
ΔlogKhat	**0.000**	0.000	0.000	0.000	**-0.237**	-0.237	-0.249	-0.237	-0.249

Table 3.3. Illustration for Idenfication of Measurement Errors

Parameters	**Model C**	col (1)	col(2)	col (3)	Model D
	$\boldsymbol{\sigma_{meK} = 0}$	$\sigma_{meK} = 0.2$	$\sigma_{meK} = 0$	$\sigma_{meK} = 0$	$\sigma_{meK} = 0.2$
	$\boldsymbol{\sigma_{meY} = 0}$	$\sigma_{meY} = 0$	$\sigma_{meY} = 0.2$	$\sigma_{meY} = 0$	$\sigma_{meY} = 0.2$
	$\boldsymbol{\sigma_{me\Pi} = 0}$	$\sigma_{me\Pi} = 0$	$\sigma_{me\Pi} = 0$	$\sigma_{me\Pi} = 0.2$	$\sigma_{me\Pi} = 0.2$
Set of Moments					
mean(Π/Y)	**0.128**	0.128	0.131	0.128	0.131
mean(log(Y/Khat))	**0.682**	0.680	0.682	0.682	0.680
mean(I/K)	**0.114**	0.117	0.114	0.114	0.117
mean(ΔlogY)	**0.050**	0.050	0.050	0.050	0.050
bsd(Π/Y)	**0.046**	0.046	0.048	0.047	0.049
wsd(Π/Y)	**0.006**	0.006	0.027	0.026	0.038
bsd(log(Y/K))	**0.703**	0.706	0.706	0.703	0.709
wsd(log(Y/K))	**0.097**	0.196	0.211	0.097	0.271
bsd(I/K)	**0.070**	0.072	0.070	0.070	0.072
wsd(I/K)	**0.117**	0.124	0.117	0.117	0.124
bsd(ΔlogY)	**0.075**	0.075	0.085	0.075	0.085
wsd(ΔlogY)	**0.166**	0.166	0.325	0.166	0.325
skew(Π/Y)	**0.712**	0.712	1.032	0.935	1.211
skew(log(Y/Khat))	**0.031**	0.024	0.027	0.031	0.020
skew(I/K)	**0.807**	1.026	0.807	0.807	1.026
skew(dlogY)	**0.298**	0.298	0.055	0.298	0.055
scorr(Π/Y)	**0.987**	0.987	0.729	0.733	0.576
scorr(log(Y/Khat))	**0.989**	0.928	0.917	0.989	0.863
scorr(I/K)	**0.379**	0.355	0.379	0.379	0.355
scorr(ΔlogY)	**0.102**	0.102	-0.324	0.102	-0.324
corr(I/K, log(Y/K))	**0.291**	0.315	0.281	0.291	0.304
corr(ΔlogY, log(Y/K))	**0.250**	0.241	0.287	0.250	0.278
Prop(I/K>0.2)	**0.308**	0.297	0.308	0.308	0.297
Prop(I/K=0)	**0.495**	0.495	0.495	0.495	0.495
Loss in TFP and Capital Stock					
ΔlogTFP	**-0.490**	-0.490	-0.490	-0.490	-0.490
ΔlogKhat	**-0.249**	-0.249	-0.249	-0.249	-0.249

Table 4. Estimation Results for UK and China

	UK		China	
Parameters	**estimate**	**s.e.**	**estimate**	**s.e.**
σ_{τ}	0.308	0.064	0.499	0.049
b^{q}	0.245	0.040	0.396	0.044
b^{i}	0.092	0.023	0.119	0.027
b^{f}	0.000	0.000	0.000	0.001
ε	24.997	1.616	24.924	1.718
$\mu_{log\beta}$	-2.425	0.021	-2.449	0.024
$\sigma_{log\beta}$	0.521	0.026	0.720	0.020
μ_{μ}	0.033	0.001	0.062	0.002
σ_{μ}	0.024	0.006	0.016	0.016
σ	0.319	0.018	0.451	0.023
σ_{meK}	0.165	0.006	0.369	0.010
σ_{meY}	0.005	0.065	0.123	0.009
$\sigma_{me\Pi}$	0.121	0.008	0.322	0.013
Set of Moments	**empirical**	**simulated**	**empirical**	**simulated**
mean(Π/Y)	0.110	0.137	0.111	0.148
mean(log(Y/Khat))	0.749	0.754	0.565	0.491
mean(I/K)	0.125	0.129	0.123	0.115
mean(ΔlogY)	0.031	0.034	0.072	0.063
bsd(Π/Y)	0.049	0.052	0.079	0.081
wsd(Π/Y)	0.028	0.017	0.052	0.053
bsd(log(Y/K))	0.541	0.619	0.778	0.898
wsd(log(Y/K))	0.214	0.155	0.349	0.351
bsd(I/K)	0.095	0.049	0.128	0.081
wsd(I/K)	0.103	0.081	0.109	0.107
bsd(ΔlogY)	0.083	0.051	0.106	0.102
wsd(ΔlogY)	0.143	0.122	0.253	0.252
skew(Π/Y)	0.801	0.827	0.690	1.407
skew(log(Y/Khat))	0.007	0.015	-0.089	0.032
skew(I/K)	2.723	0.862	2.552	2.064
skew(dlogY)	0.837	0.153	-0.045	0.076
scorr(Π/Y)	0.880	0.894	0.716	0.645
scorr(log(Y/Khat))	0.943	0.940	0.899	0.851
scorr(I/K)	0.392	0.490	0.475	0.435
scorr(ΔlogY)	0.222	0.102	-0.285	-0.177
corr(I/K, log(Y/K))	0.139	0.284	0.222	0.347
corr(ΔlogY, log(Y/K))	0.151	0.201	0.153	0.198
Prop(I/K>0.2)	0.153	0.208	0.177	0.196
Prop(I/K=0)	0.027	0.023	0.101	0.137
OI	908		825	

Table 5. Specification Tests

Parameters	benchmark	col (1)	col (2)	col (3)	col (4)	col (5)	col (6)	col (7)	col (8)	col (9)
σ_{τ}	0.499	0.289	**0.000**	0.592	0.504	0.484	0.575	**0.000**	0.800	0.543
b^{q}	0.396	**0.000**	1.099	0.747	**0.000**	0.736	1.326	0.413	0.530	0.416
b^{I}	0.119	**0.000**	0.432	0.375	0.132	**0.000**	**0.000**	0.160	0.128	0.112
b^{J}	0.000	**0.000**	0.000	0.000	0.000	0.011	**0.000**	0.000	0.000	0.000
ε	24.924	24.879	12.442	24.718	24.255	24.952	24.967	24.835	23.062	24.996
$\mu_{log\beta}$	-2.449	-2.383	-2.566	-2.579	-2.340	-2.467	-2.448	-2.490	-2.270	-2.454
$\sigma_{log\beta}$	0.720	0.729	**0.000**	0.674	0.662	0.747	0.737	0.791	**0.000**	0.699
μ_{μ}	0.062	0.070	0.069	0.068	0.035	0.069	0.065	0.067	0.059	0.065
σ_{μ}	0.016	0.000	**0.000**	0.000	0.019	0.012	0.035	0.020	0.035	**0.000**
σ	0.451	0.250	0.595	0.585	0.450	0.472	0.552	0.452	0.496	0.453
σ_{meK}	0.369	0.247	0.000	**0.000**	0.219	0.399	0.436	0.363	0.348	0.362
σ_{meY}	0.123	0.107	0.006	**0.000**	0.129	0.117	0.111	0.115	0.145	0.123
$\sigma_{me\Pi}$	0.322	0.249	0.450	**0.000**	0.316	0.318	0.336	0.314	0.450	0.328
Simulated Moments										
mean(Π/Y)	0.148	0.158	0.147	0.129	0.159	0.144	0.144	0.149	0.141	0.145
mean(log(Y/Khat))	0.491	0.443	0.588	0.605	0.354	0.543	0.530	0.529	0.328	0.499
mean(I/K)	0.115	0.152	0.116	0.115	0.095	0.125	0.120	0.121	0.111	0.118
mean(ΔlogY)	0.063	0.071	0.070	0.069	0.035	0.070	0.065	0.068	0.059	0.065
bsd(Π/Y)	0.081	0.089	0.027	0.061	0.082	0.082	0.081	0.089	0.028	0.078
wsd(Π/Y)	0.053	0.045	0.060	0.003	0.056	0.051	0.053	0.053	0.061	0.052
bsd(log(Y/K))	0.898	0.822	0.305	0.879	0.855	0.910	0.938	0.823	0.790	0.904
wsd(log(Y/K))	0.351	0.244	0.257	0.188	0.249	0.371	0.410	0.344	0.343	0.344
bsd(I/K)	0.081	0.108	0.076	0.074	0.123	0.080	0.084	0.083	0.086	0.079
wsd(I/K)	0.107	0.295	0.080	0.081	0.226	0.106	0.096	0.105	0.099	0.107
bsd(ΔlogY)	0.102	0.100	0.143	0.115	0.120	0.103	0.112	0.103	0.106	0.101
wsd(ΔlogY)	0.252	0.275	0.312	0.240	0.282	0.253	0.262	0.251	0.264	0.254
skew(Π/Y)	1.407	1.302	0.024	0.879	1.347	1.425	1.438	1.471	0.288	1.401
skew(log(Y/Khat))	0.032	0.028	-0.251	0.110	0.027	0.038	0.058	0.057	-0.024	0.032
skew(I/K)	2.064	1.062	1.027	1.401	3.663	1.659	1.768	1.892	2.026	2.049
skew(dlogY)	0.076	0.023	0.073	0.124	0.416	0.025	0.020	0.052	0.081	0.049
scorr(Π/Y)	0.645	0.755	0.007	0.998	0.625	0.665	0.642	0.689	0.007	0.626
scorr(log(Y/Khat))	0.851	0.903	0.733	0.972	0.913	0.839	0.822	0.832	0.820	0.856
scorr(I/K)	0.435	-0.069	0.629	0.596	0.183	0.419	0.467	0.453	0.505	0.430
scorr(ΔlogY)	-0.177	-0.189	-0.027	0.003	-0.133	-0.164	-0.138	-0.162	-0.215	-0.186
corr(I/K, log(Y/K))	0.347	0.294	0.901	0.370	0.289	0.381	0.413	0.379	0.369	0.348
corr(ΔlogY, log(Y/K))	0.198	0.275	0.577	0.245	0.267	0.196	0.197	0.220	0.237	0.201
Prop(I/K>0.2)	0.196	0.368	0.215	0.191	0.156	0.217	0.193	0.215	0.188	0.200
Prop(I/K=0)	0.137	0.000	0.157	0.158	0.388	0.144	0.056	0.145	0.150	0.136
OI	825	9197	7769	3319	4264	929	1158	917	3168	840

Table 6. Robustness Tests

Models	benchmark		δ = 0.045	r = 0.15	$logP^K$ = 0.1	gross profit	
Parameters	**estimate**	**s.e.**	**estimate**	**estimate**	**estimate**	**estimate**	**s.e.**
σ_{τ}	0.4993	0.0486	0.5370	0.5764	0.5617	0.4319	0.0637
b^q	0.3964	0.0441	0.4646	0.4536	0.4670	0.4554	0.0584
b^i	0.1191	0.0273	0.1297	0.1020	0.1235	0.1304	0.0426
b^f	0.0000	0.0011	0.0000	0.0000	0.0001	0.0001	0.0012
ε	24.9238	1.7176	24.9035	24.9835	24.9807	15.4996	0.9001
$\mu_{log\beta}$	-2.4493	0.0244	-2.4139	-2.3594	-2.4116	-2.1815	0.0235
$\sigma_{log\beta}$	0.7202	0.0199	0.6962	0.6760	0.6899	0.7623	0.0204
μ_{μ}	0.0623	0.0023	0.0574	0.0672	0.0652	0.0649	0.0019
σ_{μ}	0.0156	0.0158	0.0260	0.0182	0.0185	0.0193	0.0136
σ	0.4511	0.0229	0.4514	0.4518	0.4554	0.4516	0.0206
σ_{meK}	0.3690	0.0098	0.3643	0.3632	0.3668	0.3751	0.0100
σ_{meY}	0.1228	0.0094	0.1311	0.1273	0.1263	0.1107	0.0110
$\sigma_{me\Pi}$	0.3221	0.0133	0.3187	0.2992	0.3081	0.2153	0.0108
Set of Moments	**empirical**	**simulated**	**simulated**	**simulated**	**simulated**	**empirical**	**simulated**
mean(Π/Y)	0.1109	0.1476	0.1493	0.1539	0.1491	0.2319	0.2049
mean(log(Y/Khat))	0.5651	0.4911	0.5277	0.5626	0.5579	0.5651	0.2443
mean(I/K)	0.1232	0.1155	0.1218	0.1212	0.1188	0.1232	0.1190
mean(ΔlogY)	0.0719	0.0627	0.0578	0.0676	0.0656	0.0719	0.0654
bsd(Π/Y)	0.0793	0.0814	0.0803	0.0813	0.0794	0.1070	0.1098
wsd(Π/Y)	0.0522	0.0527	0.0530	0.0514	0.0510	0.0530	0.0513
bsd(log(Y/K))	0.7775	0.8975	0.8973	0.9019	0.9072	0.7775	0.9000
wsd(log(Y/K))	0.3494	0.3505	0.3475	0.3438	0.3486	0.3494	0.3573
bsd(I/K)	0.1282	0.0811	0.0834	0.0826	0.0812	0.1282	0.0833
wsd(I/K)	0.1091	0.1071	0.1049	0.1076	0.1060	0.1091	0.1089
bsd(ΔlogY)	0.1058	0.1017	0.1028	0.1005	0.1014	0.1058	0.1068
wsd(ΔlogY)	0.2529	0.2522	0.2571	0.2507	0.2532	0.2529	0.2560
skew(Π/Y)	0.6898	1.4071	1.3913	1.3451	1.3656	0.7321	1.2754
skew(log(Y/Khat))	-0.0890	0.0317	0.0296	0.0256	0.0289	-0.0890	0.0434
skew(I/K)	2.5515	2.0641	1.9465	1.9836	2.0365	2.5515	2.0123
skew(dlogY)	-0.0453	0.0756	0.0662	0.0694	0.0721	-0.0453	0.0726
scorr(Π/Y)	0.7164	0.6453	0.6352	0.6563	0.6483	0.8149	0.7842
scorr(log(Y/Khat))	0.8992	0.8506	0.8528	0.8562	0.8547	0.8992	0.8484
scorr(I/K)	0.4749	0.4351	0.4547	0.4416	0.4390	0.4749	0.4378
scorr(ΔlogY)	-0.2848	-0.1771	-0.1931	-0.1882	-0.1855	-0.2848	-0.1423
corr(I/K, log(Y/K))	0.2221	0.3471	0.3481	0.3449	0.3445	0.2221	0.3670
corr(ΔlogY, log(Y/K))	0.1530	0.1977	0.1976	0.1953	0.1945	0.1530	0.2062
Prop(I/K>0.2)	0.1767	0.1963	0.2099	0.2081	0.2015	0.1767	0.2067
Prop(I/K=0)	0.1008	0.1366	0.1326	0.1313	0.1336	0.1008	0.1336
OI	825		870	920	879	715	

Table 7. Losses in Aggregate TFP and Capital Stock

7.1. Simulation for UK

type	β	μ	ΔlogTFP	ΔlogK	1-γ	ΔlogY
1	0.047	0.004	-0.103	-0.052	0.529	-0.076
2	0.047	0.033	-0.103	-0.073	0.529	-0.087
3	0.047	0.062	-0.102	-0.086	0.529	-0.093
4	0.089	0.004	-0.250	-0.084	0.680	-0.137
5	0.089	0.033	-0.250	-0.107	0.680	-0.153
6	0.089	0.062	-0.249	-0.122	0.680	-0.162
7	0.167	0.004	-0.550	-0.135	0.801	-0.218
8	0.167	0.033	-0.547	-0.169	0.801	-0.244
9	0.167	0.062	-0.545	-0.179	0.801	-0.252
average	0.101	0.033	-0.300	-0.112	0.670	-0.174

7.2. Simulation for China

type	β	μ	ΔlogTFP	ΔlogK	1-γ	ΔlogY
1	0.036	0.043	-0.166	-0.109	0.461	-0.140
2	0.036	0.062	-0.168	-0.127	0.461	-0.149
3	0.036	0.081	-0.168	-0.132	0.461	-0.151
4	0.086	0.043	-0.480	-0.178	0.674	-0.277
5	0.086	0.062	-0.488	-0.193	0.674	-0.289
6	0.086	0.081	-0.483	-0.217	0.674	-0.304
7	0.208	0.043	-0.936	-0.305	0.833	-0.410
8	0.208	0.062	-0.939	-0.326	0.833	-0.429
9	0.208	0.081	-0.938	-0.344	0.833	-0.444
average	0.110	0.062	-0.530	-0.215	0.656	-0.323

7.3. Simulation for China using UK as Counterfactual

type	β	μ	ΔlogTFP	ΔlogK	1-γ	ΔlogY
1	0.036	0.043	-0.070	-0.085	0.461	-0.077
2	0.036	0.062	-0.070	-0.098	0.461	-0.083
3	0.036	0.081	-0.070	-0.102	0.461	-0.085
4	0.086	0.043	-0.241	-0.136	0.674	-0.170
5	0.086	0.062	-0.243	-0.145	0.674	-0.177
6	0.086	0.081	-0.241	-0.165	0.674	-0.190
7	0.208	0.043	-0.672	-0.224	0.833	-0.299
8	0.208	0.062	-0.674	-0.243	0.833	-0.315
9	0.208	0.081	-0.672	-0.256	0.833	-0.325
average	0.110	0.062	-0.328	-0.161	0.656	-0.219

7.4. Gain from Improvement for China

type	β	μ	ΔΔlogTFP	ΔΔlogK	1-γ	ΔΔlogY
1	0.036	0.043	0.096	0.024	0.461	0.063
2	0.036	0.062	0.097	0.029	0.461	0.066
3	0.036	0.081	0.097	0.030	0.461	0.066
4	0.086	0.043	0.240	0.043	0.674	0.107
5	0.086	0.062	0.244	0.048	0.674	0.112
6	0.086	0.081	0.242	0.052	0.674	0.114
7	0.208	0.043	0.264	0.080	0.833	0.111
8	0.208	0.062	0.265	0.083	0.833	0.114
9	0.208	0.081	0.266	0.089	0.833	0.118
average	0.110	0.062	0.201	0.053	0.656	0.104

Table 8. Regression for $E_t [log(Y_{i,t}/K_{i,t})]$ in China

	baseline	size	ownship	location	manager	full
$E_t [\Pi_{i,t}/Y_{i,t}]$	**-3.298**	**-3.267**	**-3.115**	**-3.154**	**-3.258**	**-2.938**
	(0.160)	(0.160)	(0.132)	(0.132)	(0.162)	(0.159)
$E_t [I_{i,t}/K_{i,t}]$	**1.199**	**1.139**	**1.343**	**1.081**	**1.169**	**1.150**
	(0.078)	(0.078)	(0.082)	(0.084)	(0.077)	(0.079)
firm age	**0.012**	**0.012**	**0.004**	**0.010**	**0.012**	**0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SMALL		**0.126**				**0.146**
		(0.032)				(0.033)
MEDIUM		**0.032**				**0.024**
		(0.025)				(0.025)
PRIVATE			**0.617**			**0.653**
			(0.105)			(0.120)
STATE			**0.490**			**0.529**
			(0.037)			(0.038)
SHAREHOLDING			**0.171**			**0.271**
			(0.039)			(0.041)
FOREIGN			**0.176**			**0.261**
			(0.070)			(0.070)
JIANGSU				**0.340**		**0.368**
				(0.028)		(0.031)
SICHUAN				**0.137**		**0.183**
				(0.030)		(0.031)
SHANXI				**0.138**		**0.156**
				(0.030)		(0.030)
manager age					**0.000**	**0.003**
					(0.002)	(0.002)
manager education					**-0.049**	**0.001**
					(0.018)	(0.018)
manager experience					**0.003**	**0.002**
					(0.001)	(0.001)
NOPARTYMEMBERSHIP					**0.066**	**0.149**
					(0.055)	(0.058)

Note:

1. The baseline group is LARGE, COLLECTIVE, JILIN, and PARTYMEMBERSHIP.
2. Robust standard errors are reported in ( ).