7 Appendix

7.1 Aggregate TFPR Gains

We first transform gross output into value added. Define value added as $\hat{Y}_{i,t} \equiv \max_{M_{i,t}} \{Y_{i,t} - m_{i,t}M_{i,t}\}$. This yields

$$\begin{aligned}\hat{Y}_{i,t} &= (1-(1-\alpha_i-\beta_i)(1-\eta_i))\left[\frac{(1-\alpha_i-\beta_i)(1-\eta_i)}{m_{i,t}}\right]^{\frac{(1-\alpha_i-\beta_i)(1-\eta_i)}{1-(1-\alpha_i-\beta_i)(1-\eta_i)}} \\ &\quad \left(\hat{Z}_{i,t}^{\frac{\eta_i}{1-\eta_i}}\hat{K}_{i,t}^{\alpha_i}L_{i,t}^{\beta_i}\right)^{\frac{(1-\eta_i)}{1-(1-\alpha_i-\beta_i)(1-\eta_i)}},\end{aligned}$$

where $\hat{Z}_{i,t} \equiv X_{i,t}A_{i,t}^{\frac{1}{\eta_i}-1}$. We then calculate efficiency gain from capital reallocation within each type of firms associated with the same α_i and η_i. The aggregate output gain is obtained by averaging the gain across different types of firms.

For notational convenience, consider an economy in which all firms have the same α, η and, thus, γ. Efficient capital allocation features identical MRPK across firms. Without loss of generality, we drop time subscript. For simplicity, we assume away labor and intermediate input distortions such that $w_i = w$ and $m_i = m$. Value-added would, thus, follow

$$\hat{Y}_i = \left(\hat{Z}_i^{\frac{\eta}{1-\eta}}\hat{K}_i^{\alpha}L_i^{\beta}\right)^{\frac{(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)}}, \tag{32}$$

where irrelevant terms are omitted.

Denote L_i^* and $\hat{K}_i^*$ firm i's labor and productive capital in the efficient allocation. (14) implies $\hat{K}_i^* \propto \hat{Z}_i$. Using (5) to (8), together with the fact that $\hat{K}_i^* \propto \hat{Z}_i$, we have $L_i^* \propto \hat{Z}_i$. Define $\hat{K} \equiv \sum_i \hat{K}_i^*$ and $L \equiv \sum_i L_i^*$ as the total productive capital and labor, respectively. (32) implies that the total value added in the efficient allocation is equal to

$$\hat{Y}^* = \left(\hat{K}^{\alpha}L^{\beta}\right)^{\frac{(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)}} \times \frac{\sum_i \hat{Z}_i}{\left(\sum_i \hat{Z}_i\right)^{\frac{(\alpha+\beta)(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)}}}. \tag{33}$$

We omit irrelevant constant terms.

Now we turn to the actual total value added in the economy with capital distortions. (14) implies $\hat{K}_i \propto \hat{Z}_i/(1+\tau_i)^{\frac{\eta+\alpha(1-\eta)}{\eta}}$. Moreover, (5) to (8) establish that $L_i \propto \hat{Z}_i/(1+\tau_i)^{\frac{\alpha(1-\eta)}{\eta}}$. Then, the actual total value added follows

$$\hat{Y} = \left(\hat{K}^{\alpha}L^{\beta}\right)^{\frac{(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)}} \times \frac{\sum_i \frac{\hat{Z}_i}{(1+\tau_i)^{\frac{\alpha(1-\eta)}{\eta}}}}{\left[\left(\sum_i \frac{\hat{Z}_i}{(1+\tau_i)^{\frac{\eta+\alpha(1-\eta)}{\eta}}}\right)^{\alpha}\left(\sum_i \frac{\hat{Z}_i}{(1+\tau_i)^{\frac{\alpha(1-\eta)}{\eta}}}\right)^{\beta}\right]^{\frac{(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)}}}. \tag{34}$$

The efficiency gain from capital reallocation can, thus, be represented by the difference between $\hat{Y}^*$ and $\hat{Y}$:

$$\begin{aligned}\log \hat{Y}^* - \log \hat{Y} &= \frac{\alpha(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)} \log \frac{\sum_i \frac{\hat{Z}_i}{(1+\tau_i)^{\frac{\eta+\alpha(1-\eta)}{\eta}}}}{\sum_i \hat{Z}_i} \\ &\quad - \frac{\eta+\alpha(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)} \log \frac{\sum_i \frac{\hat{Z}_i}{(1+\tau_i)^{\frac{\alpha(1-\eta)}{\eta}}}}{\sum_i \hat{Z}_i}.\end{aligned}$$

With a large number of firms, the efficiency gain can be approximated by:

$$\log \hat{Y}^* - \log \hat{Y} \approx \frac{1}{2}\frac{\alpha(1-\eta)}{\eta}\frac{\eta+\alpha(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)} Var\left[\log(1+\tau_i)\right]. \tag{35}$$

(35) shows that the efficiency gain from removing capital misallocation is proportional to the variance of $\log(1+\tau_i)$.

Now we aggregate the efficiency gain across different firm types.

$$\text{Aggregate output gain} = \log \int \hat{Y}^*(j)\,\psi(j) - \log \int \hat{Y}(j)\,\psi(j),$$

where $\psi(j)$ represents the density for the number of firms associated with $\alpha(j)$ and $\eta(j)$.

7.1.1 Labor Market Distortions

We now introduce labor distortions but maintain the assumption that intermediate inputs are efficiently allocated. (14) implies $\hat{K}_i \propto \hat{Z}_i / \left((1+\tau_i)^{\frac{\eta+\alpha(1-\eta)}{\eta}} \left(1+\tau_i^L\right)^{\frac{\beta(1-\eta)}{\eta}}\right)$. Equations (5), (26), together with (7) and (8), imply that $L_i \propto \hat{Z}_i / \left((1+\tau_i)^{\frac{\alpha(1-\eta)}{\eta}} \left(1+\tau_i^L\right)^{\frac{\beta(1-\eta)+\eta}{\eta}}\right)$. Therefore, the total value added with both capital and labor distortions follows

$$\begin{aligned}\hat{Y}^L &= \left(\hat{K}^\alpha L^\beta\right)^{\frac{(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)}} \times \\ &\quad \frac{\sum \frac{\hat{Z}_i}{(1+\tau_i)^{\frac{\alpha(1-\eta)}{\eta}}\left(1+\tau_i^L\right)^{\frac{\beta(1-\eta)}{\eta}}}}{\left[\left(\sum_i \frac{\hat{Z}_{i,t}}{(1+\tau_i)^{\frac{\eta+\alpha(1-\eta)}{\eta}}\left(1+\tau_i^L\right)^{\frac{\beta(1-\eta)}{\eta}}}\right)^\alpha \left(\sum_i \frac{\hat{Z}_{i,t}}{(1+\tau_i)^{\frac{\alpha(1-\eta)}{\eta}}\left(1+\tau_i^L\right)^{\frac{\beta(1-\eta)+\eta}{\eta}}}\right)^\beta\right]^{\frac{(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)}}}.\end{aligned}$$

Efficient allocation features identical marginal revenue products of both capital and labor across firms. It is immediate that the total value added in the efficient allocation is identical to that in (33). The efficiency gain from reallocation can thus be approximated by

$$\begin{aligned}\log \hat{Y}^* - \log \hat{Y}^L &\approx \frac{1}{2}\frac{\alpha(1-\eta)}{\eta}\frac{\eta+\alpha(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)} Var\left[\log(1+\tau_i)\right] \\ &\quad + \frac{1}{2}\frac{\beta(1-\eta)}{\eta}\frac{\eta+\beta(1-\eta)}{1-(1-\alpha-\beta)(1-\eta)} Var\left[\log\left(1+\tau_i^L\right)\right],\end{aligned} \tag{36}$$

where we assume that τ_i and τ_i^L are uncorrelated. The second term on the right-hand side of (36) captures the welfare gain from correcting labor misallocation.

7.2 Investment Decision

The investment problem is defined by the stochastic Bellman equation:

$$V(Z_{i,t}, K_{i,t}) = \max_{I_{i,t}} \left\{ \pi(Z_{i,t}, K_{i,t}; I_{i,t}) - P_{i,t}^K I_{i,t} - G(K_{i,t}; I_{i,t}) + \frac{1}{1+r} E_t \left[V(Z_{i,t+1}, K_{i,t+1}) \right] \right\}, \tag{37}$$

where $Z_{i,t+1}$ and $K_{i,t+1}$ follow the law of motion (19) and (12), respectively. When $G(Z_{i,t}, K_{i,t}; I_{i,t}) = 0$, the optimal investment rate is a linear function of $Z_{i,t}/K_{i,t}$:

$$\frac{I_{i,t}}{K_{i,t}} = \left[\frac{1-\gamma_i}{(1+\tau_i)\, J_t} \right]^{\frac{1}{\gamma_i}} \left(\frac{Z_{i,t}}{K_{i,t}} \right) - 1, \tag{38}$$

which leads to (14). When $G(K_{i,t}; I_{i,t}) > 0$, the investment policy can be solved numerically. Wu (2014) provides further details.

7.3 China Data

Brandt et al. (2012) provide an excellent description of the dataset and implement a series of consistency checks. We strictly follow them in constructing a panel and cleaning the data. A few things deserve attention. The first is how to construct capital data. The survey does not contain information on investment expenditures. However, firms report the book value of their fixed capital stock at original purchase prices. Since these book values are the sum of nominal values from different years, they should not be used directly. To construct the real capital stock series, we use the following formula:

$$K_{i,t} = (1-\delta) K_{i,t-1} + \frac{BK_{i,t} - BK_{i,t-1}}{P_t},$$

where $BK_{i,t}$ is the gross book value of capital stock for firm i in year t; P_t is the price index of investment in fixed assets in year t constructed by Perkins and Rawski (2008). The initial book value of capital stock is taken directly from the dataset for firms founded later than 1998. For firms founded before 1998, we predict it to be

$$BK_{i,t_0} = \frac{BK_{i,t_1}}{(1+g_i)^{t_1 - t_0}},$$

where BK_{i,t_0} is the projected initial book value of capital stock when firm i was born in year t_0; BK_{i,t_1} is the book value of capital stock when firm i first appears in our dataset in year t_1; and g_i is the average capital stock growth rate of firm i for the period we observe in the data since year t_1.

The calibration of δ is based on the law of motion of capital (12), which implies that

$$\begin{aligned}\log\left(1+\frac{I_{i,t}}{K_{i,t}}\right) &= \triangle\log\hat{K}_{i,t}-\log\left(1-\delta\right)\\ &\simeq \triangle\log\hat{K}_{i,t}+\delta.\end{aligned}$$

The model implies that both $\hat{K}_{i,t}$ and $Y_{i,t}$ grow at the same rate in the long run.[28] So, the above equation suggests calibrating δ by matching the difference between $\log\left(1+I_{i,t}/K_{i,t}\right)$ and $\Delta\log Y_{i,t}$. This gives $\delta=0.05$. Investment expenditure $I_{i,t}$ is then recovered according to equation (12).

Four key variables for estimation are then constructed by definition: profit-revenue ratio, $(\pi_{i,t}/Y_{i,t})$, log revenue-capital ratio, $\left(\log\left(Y_{i,t}/\hat{K}_{i,t}\right)\right)$, investment rate, $(I_{i,t}/K_{i,t})$, and revenue growth rate, $(\Delta\log Y_{i,t})$. The revenue and profit data are deflated by the GDP deflator for the secondary industry from the *China Statistical Yearbook*. We exclude outliers by trimming the top and bottom 5 percent of observations for each variable in each year. The model assumes that firms are on the balanced-growth path. In the presence of capital adjustment costs, however, it would take years for firms to reach their balanced-growth path. Therefore, we exclude firms that are less than 5 years old when they first enter our dataset. Furthermore, our investment model does not consider entry and exit, which means that the model's implications are valid only for existing and ongoing firms. Finally, many existing non-state-owned firms with sales revenue beyond RMB 5 millions were missing from the survey in the early years but have appeared in the NBS data since 2004 thanks to the economic census conducted in that year. For these reasons, our empirical exercise utilizes a sample of firms surviving from 2004 to 2007 and being at least 5 years old in 2004. This gives us a balanced panel consisting of 107,579 firms and spanning 4 years. The annual mean values of each of the four variables in the balanced panel are reported in Table A.3.

[Insert Table A.3]

Our simulations in the structural estimation assume firms to be around their balanced growth paths. Since the estimation is to match moments of the four variables, we need to check the stationarity of the four variables from a fast-changing economy like China's. It is hard to give a formal test, given the fact that the panel has only four time-series observations. Nevertheless, one can still see from Table A.3 that except for the falling investment rate, none of the other three variables features an obvious trend.

[28] This result carries over to the case with capital adjustment costs. Bloom (2000) shows that when a firm is on its balanced growth path, the gap between capital stock with and without adjustment costs is bounded.

7.4 Compustat Data

We construct capital stock and deflate the data strictly following Bloom (2009). To be specific, capital stocks for firm i in industry m in year t are constructed by the perpetual inventory method: $K_{i,t} = (1-\delta) K_{i,t-1} (P_{m,t}/P_{m,t-1}) + I_{i,t}$, initialized using the net book value of capital, where $\delta = 0.10$, $I_{i,t}$ is net capital expenditures on plant, property, and equipment, and $P_{m,t}$ is the industry-level capital goods deflator from Bartelsman et al. (2000). Sales revenue and cost of goods sold are deflated by the CPI. We use a sample from 2002 to 2005 since $P_{m,t}$ is not available after 2005. Finally, we also trim the top and bottom 5 percent of observations for each variable in each year in Compustat.

7.5 Back-of-the-Envelope Calculations for the Effects of Market Beta and Market Incompleteness

We back out the following distribution of τ_i:

$$\log(1+\tau_i) \overset{i.i.d.}{\sim} N\left(0, 0.684^2\right).$$

Suppose that all the heterogeneity comes from J_i or, more precisely, r_i, the firm-specific discount factor. $\log J_i$ would follow a log-normal distribution with variance of 0.684^2. Since $\log J_i \simeq \log(r_i + \delta)$, it implies that

$$\log(r_i + \delta) \overset{i.i.d.}{\sim} N\left(\log(0.25), 0.684^2\right).$$

We can, thus, back out $var(r_i) = 0.244^2$.

Risk-averse investors would assign higher discount rates to firms with $Z_{i,t}$ that are more correlated to aggregate shocks. To see the capacity of market beta in generating $var(r_i)$, consider a typical CAPM,

$$r_i = r_f + (r_m - r_f) \cdot beta_i,$$

where r_f is the interest rate on riskless assets, r_m is the expected market return and $r_m - r_f$ is the expected market risk premium.

If all the heterogeneity in r_i is driven by heterogeneous market beta, $var(beta_i)$ has to be 2.44^2 to match $var(r_i) = 0.244^2$ with a 10 percent risk premium. Since few firms in the NBS data are listed, we cannot calculate the dispersion of market beta. Morck et al. (2000) find the stock returns in emerging economies to be more synchronous, probably due to a poor capitalization of firm-specific information. This implies that the market betas tend to be less dispersed in emerging economics than those in developed economies. Picking up the number from Mankiw and Shapiro (1986), $var(beta_i)$ is 0.38^2 for 464 U.S. stocks over 92 quarters.

Even if we take this value as the upper limit for $var\left(beta_i\right)$ in China, $var\left(r_i\right)$ would be 0.038^2, merely 2.4 percent of the 0.244^2 that is needed to explain the estimated σ_τ^2.

To see the importance of market incompleteness in generating heterogeneity in r_i, we adopt the framework in Angeletos and Panousi (2011). Following their notations in equation (18), we have

$$r_i = r_f + \sqrt{\frac{2\theta\gamma\left(d - r_f\right)}{\theta + 1}}\sigma_i,$$

where $d > 0$ is the discount factor, $\gamma > 0$ is the coefficient of relative risk aversion, and $\theta > 0$ is the elasticity of intertemporal substitution. What we need is a measure of σ_i and its dispersion in the data.

Assume that $Z_{i,t}$ follows the stochastic process in (19), where σ_i parameterizes the risk level for firm i. Bloom (2000) shows that revenue and capital will still grow at the same rate of μ in the long run. This implies

$$\begin{aligned} \Delta \log Y_{i,t} &= \Delta \log Z_{i,t} \\ &= \mu + z_{i,t} - z_{i,t-1} \\ &\simeq \mu + e_{i,t}, \end{aligned}$$

if $\rho \rightarrow 1$. Therefore, when panel data are available, the variance of a firm's sales growth, $var\left(\Delta \log Y_{i,t}\right)$, serves as a proxy for its risk level, σ_i^2.

In the NBS sample, the value of $var\left(\Delta \log Y_{i,t}\right)$ has an estimate of 0.142^2. If all the heterogeneity in J_i is driven by idiosyncratic risks, $\sqrt{2\theta\gamma\left(d - r_f\right)/\left(\theta + 1\right)}$ should be as large as 1.718. If $d - r_f = 0.10$ and $\theta = 1$, the coefficient of relative risk aversion γ has to be as large as 30 to match $var\left(r_i\right) = 0.244^2$. Alternatively, if $\theta = 1$ and $\gamma = 5$, then $var\left(r_i\right)$ would be equal to 0.1^2, which accounts for about 16.9 percent of the estimated σ_τ^2.

7.6 The Simulated Methods of Moments

The SMM estimator Θ^* solves the following minimal quadratic distance problem (Gouriéroux and Monfort, 1996):

$$\Theta^* = \arg\min_{\Theta} \left(\hat{\Phi}^D - \frac{1}{S}\sum_{s=1}^{S} \hat{\Phi}_s^M\left(\Theta\right)\right)' \Omega \left(\hat{\Phi}^D - \frac{1}{S}\sum_{s=1}^{S} \hat{\Phi}_s^M\left(\Theta\right)\right), \tag{39}$$

where Θ is the vector of parameters of interest; $\hat{\Phi}^D$ is a set of empirical moments estimated from an empirical dataset; $\hat{\Phi}^M\left(\Theta\right)$ is the same set of simulated moments estimated from a simulated dataset based on the model; S is the number of simulation paths; and Ω is a positive definite weighting matrix. See Wu (2009) for the technical details on how to solve the minimal quadratic distance problem of (39), to draw optimal weighting matrix from the data and to calculate the numerical standard errors for the estimates.

Suppose that the empirical dataset is a panel with N firms and T years. We use the asymptotics of fixed T and large N. At the efficient choice for Ω^*, the SMM procedure provides a global specification test of the overidentifying restrictions of the model:

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

7.7 Robustness Tests

Table A.4 presents results for a set of robustness checks. Column (1) corresponds to the benchmark model, where $r = 0.20$ and $\rho = 0.90$. Columns (2) and (3) test the sensitivity to the discount factor by imposing $r = 0.15$ and 0.25, respectively. Columns (4) and (5) report the results with $\rho = 0.85$ and 0.95, respectively. Overall, we see only some modest variations in the estimates. In particular, the estimated σ_τ, ranging from 0.67 to 0.75, appears to be robust to the alternative choices of r and ρ.

[Insert Table A.4]

Column (6) increases the number of type in each dimension of heterogeneity from 3 to 5. The alternative simulation specification triples the estimation time but causes virtually no change in any of the estimates.

Columns (7) and (8) allow the long-run growth rate of $Z_{i,t}$, μ, and the level of uncertainty, σ, to be firm-specific. In Column (7), μ_i follows a normal distribution with mean μ and standard deviation σ_μ. In Column (8), σ_i follows a normal distribution with mean σ and standard deviation σ_σ. Introducing an additional dimension of heterogeneity involves an additional state variable. The estimation time increases by 2.5 times accordingly. Not surprisingly, allowing more heterogeneities improves the overall fitness. The estimate of σ_τ, however, is almost unaffected.

Column (9) replaces measurement errors in capital with measurement errors in investment. To be specific, $K_{i,t+1} = (1-\delta)(K_{i,t} + I_{i,t})$, where $I_{i,t} = I_{i,t}^{true}\exp\left(e_{i,t}^I\right)$ and $e_{i,t}^I \overset{i.i.d}{\sim} N(0, \sigma_{meI}^2)$. The alternative specification implies a persistent effect on the measurement of capital through capital accumulation. We find much larger capital adjustment costs. The estimated σ_τ, however, increases little, by less than 5 percent.

7.8 Specification Tests

To evaluate the importance of each of the three components (i.e., the unobserved heterogeneities, capital adjustment costs and measurement errors), Table A.5 reports specification tests for three restricted models. The full-blown model is taken as the benchmark, with estimation results listed in Column (1).

[Insert Table A.5]

Column (2) reports the results with homogeneous α_i and η_i – i.e., $\sigma_{\log\alpha} = \sigma_{\log\eta} = 0$. The estimated σ_τ increases from 0.706 to 0.924, implying a large bias by omitting the unobserved heterogeneities. Moreover, the model fails to match the data in a number of aspects, including all moments of the profit-revenue ratio (except for the mean) and the correlation between the revenue-capital and profit-revenue ratio. As a result, the overall fitness of the restricted model degenerates substantially.

Column (3) reports the results with no capital adjustment costs – i.e., $b^q = b^i = b^f = 0$. The estimate for σ_τ is just 7 percent lower than the benchmark result. For reasons discussed in the text, the unobserved heterogeneities can essentially be identified by the five core moments, on which capital adjustment costs have little impact. Nevertheless, without capital adjustment costs, the model cannot match some salient features, such as positive serial correlation, in the investment rate and revenue growth.

Column (4) reports the results with no measurement errors – i.e., $\sigma_{meK} = \sigma_{meY} = \sigma_{me\pi} = 0$. The estimate for σ_τ is, once again, very close to the benchmark result, with a difference of 3 percent. Like capital adjustment costs, measurement errors have only second-order effects on the between-group standard deviations. Consequently, the estimation of the unobserved heterogeneities is largely unaffected by measurement errors. Regarding the fitness, the restricted model generates too small within-group standard deviations of the profit-revenue and revenue-capital ratios and too much serial correlation in these two ratios.

Appendix for Tables

Table A.1: Illustration for Identification of Capital Adjustment Costs

Parameters	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	$\boldsymbol{b^q = 0.0}$	$\boldsymbol{b^q = 1.0}$	$b^q = 0.0$	$b^q = 0.0$	$b^q = 1.0$
	$\boldsymbol{b^i = 0.0}$	$b^i = 0.0$	$\boldsymbol{b^i = 0.1}$	$b^i = 0.0$	$b^i = 0.1$
	$\boldsymbol{b^f = 0.0}$	$b^f = 0.0$	$b^f = 0.0$	$\boldsymbol{b^f = 0.1}$	$b^f = 0.1$
Set of Moments					
mean(π/Y)	0.170	0.170	0.170	0.170	0.170
mean(log(Y/Khat))	0.837	0.865	0.780	0.852	1.006
mean(I/K)	0.202	0.111	0.137	0.187	0.112
mean(ΔlogY)	0.050	0.049	0.050	0.051	0.048
bsd(π/Y)	0.061	0.061	0.061	0.061	0.061
wsd(π/Y)	0.000	0.000	0.000	0.000	0.000
bsd(log(Y/Khat))	0.682	0.676	0.682	0.689	0.674
wsd(log(Y/Khat))	0.009	**0.131**	**0.096**	**0.124**	0.128
bsd(I/K)	0.233	0.080	0.170	0.266	0.098
wsd(I/K)	0.451	**0.065**	**0.242**	0.505	0.114
bsd(ΔlogY)	0.216	0.135	0.171	0.188	0.142
wsd(ΔlogY)	0.336	0.190	0.232	0.270	0.199
skew(π/Y)	0.176	0.176	0.176	0.176	0.176
skew(log(Y/Khat))	0.000	0.036	0.019	0.059	0.039
skew(I/K)	1.412	0.674	**2.712**	**3.380**	1.376
skew(dlogY)	0.000	0.037	0.431	0.774	0.200
scorr(π/Y)	1.000	1.000	1.000	1.000	1.000
scorr(log(Y/Khat))	1.000	0.967	0.980	0.967	0.968
scorr(I/K)	-0.058	**0.619**	**0.184**	-0.049	0.331
scorr(ΔlogY)	-0.067	0.009	0.043	0.001	0.013
bcorr(π/Y, log(Y/Khat))	-0.379	-0.392	-0.383	-0.376	-0.381

Note: The imposed parameter values are $\delta = 0.05$, $r = 0.15$, $\mu_{log\alpha} = \mu_{log\eta} = -2.50$, $\sigma_{log\alpha} = \sigma_{log\eta} = 0.50$, $\rho = 0.90$, $\mu = 0.05$, $\sigma = 0.40$, and $\sigma_{meK} = \sigma_{meY} = \sigma_{me\pi} = 0$.

Table A.2: Illustration for Identification of Measurement Errors

Parameters	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	$\boldsymbol{\sigma_{meK}}$ **= 0.0**	$\boldsymbol{\sigma_{meK}}$ **= 0.5**	σ_{meK} = 0.0	σ_{meK} = 0.0	σ_{meK} = 0.5
	$\boldsymbol{\sigma_{meY}}$ **= 0.0**	σ_{meY} = 0.0	$\boldsymbol{\sigma_{meY}}$ **= 0.5**	σ_{meY} = 0.0	σ_{meY} = 0.5
	$\boldsymbol{\sigma_{me\pi}}$ **= 0.0**	$\sigma_{me\pi}$ = 0.0	$\sigma_{me\pi}$ = 0.0	$\boldsymbol{\sigma_{me\pi}}$ **= 0.5**	$\sigma_{me\pi}$ = 0.5
Set of Moments					
mean(π/Y)	0.170	0.170	0.193	0.170	0.193
mean(log(Y/Khat))	1.006	0.996	1.007	1.006	0.997
mean(I/K)	0.112	0.127	0.112	0.112	0.127
mean(ΔlogY)	0.048	0.048	0.048	0.048	0.048
bsd(π/Y)	0.061	0.061	0.088	0.066	0.094
wsd(π/Y)	0.000	0.000	**0.094**	**0.045**	0.111
bsd(log(Y/Khat))	0.674	0.711	0.720	0.674	0.755
wsd(log(Y/Khat))	0.128	**0.416**	**0.451**	0.128	0.600
bsd(I/K)	0.098	0.125	0.098	0.098	0.125
wsd(I/K)	0.114	**0.163**	0.114	0.114	0.163
bsd(ΔlogY)	0.142	0.142	0.276	0.142	0.276
wsd(ΔlogY)	0.199	0.199	**0.695**	0.199	0.695
skew(π/Y)	0.176	0.176	1.989	0.706	2.284
skew(log(Y/Khat))	0.039	-0.021	0.016	0.039	-0.016
skew(I/K)	1.376	2.871	1.376	1.376	2.871
skew(dlogY)	0.200	0.200	0.006	0.200	0.006
scorr(π/Y)	1.000	1.000	**0.288**	**0.575**	0.227
scorr(log(Y/Khat))	0.968	**0.669**	**0.634**	0.968	0.490
scorr(I/K)	0.331	0.229	0.331	0.331	0.229
scorr(ΔlogY)	0.013	0.013	**-0.445**	0.013	-0.445
bcorr(π/Y, log(Y/Khat))	-0.381	-0.359	-0.474	-0.351	-0.423

Note: The imposed parameter values are δ = 0.05, r = 0.15, $\mu_{log\alpha} = \mu_{log\eta}$ = –2.50, $\sigma_{log\alpha} = \sigma_{log\eta}$ = 0.50, ρ = 0.90, μ = 0, σ = 0.40, b^q =1.0, and $b^i = b^f$ = 0.1.

Table A.3: The 2004-2007 Balanced Panel for NBS Firms

Year	2004	2005	2006	2007
No. of firms	107579	107579	107579	107579
mean(π/Y)	0.155	0.159	0.157	0.160
mean(log(Y/Khat))	1.143	1.145	1.129	1.134
mean(I/K)	..	0.187	0.161	0.144
mean(ΔlogY)	..	0.109	0.083	0.097

Table A.4: Robustness Tests

Parameters	(1) benchmark	(2) r = 0.15	(3) r = 0.25	(4) ρ = 0.85	(5) ρ = 0.95
σ_τ	0.714	0.670	0.746	0.712	0.729
$\mu_{log\alpha}$	-2.606	-2.727	-2.496	-2.595	-2.602
$\sigma_{log\alpha}$	0.557	0.606	0.524	0.559	0.549
$\mu_{log\eta}$	-2.808	-2.672	-2.973	-2.826	-2.812
$\sigma_{log\eta}$	0.725	0.666	0.794	0.729	0.730
b^q	0.278	0.387	0.273	0.258	0.346
b^i	0.000	0.000	0.005	0.000	0.014
b^f	0.034	0.060	0.025	0.024	0.029
μ	0.080	0.080	0.083	0.081	0.085
σ	0.425	0.412	0.447	0.427	0.416
σ_{meK}	0.401	0.379	0.410	0.405	0.411
σ_{meY}	0.001	0.000	0.001	0.000	0.004
$\sigma_{me\pi}$	0.578	0.575	0.579	0.581	0.574
Moments					
mean(π/Y)	0.154	0.153	0.155	0.154	0.154
mean(log(Y/Khat))	1.146	1.127	1.165	1.143	1.159
mean(I/K)	0.173	0.170	0.177	0.174	0.179
mean(ΔlogY)	0.080	0.080	0.083	0.081	0.084
bsd(π/Y)	0.075	0.075	0.074	0.074	0.075
wsd(π/Y)	0.049	0.049	0.049	0.049	0.049
bsd(log(Y/Khat))	0.878	0.874	0.882	0.879	0.884
wsd(log(Y/Khat))	0.332	0.319	0.337	0.333	0.337
bsd(I/K)	0.164	0.153	0.170	0.155	0.178
wsd(I/K)	0.215	0.209	0.215	0.217	0.214
bsd(ΔlogY)	0.163	0.160	0.165	0.158	0.168
wsd(ΔlogY)	0.219	0.222	0.215	0.224	0.211
skew(π/Y)	0.854	0.856	0.846	0.855	0.857
skew(log(Y/Khat))	0.004	0.007	0.006	0.002	-0.002
skew(I/K)	2.251	2.320	2.206	2.168	2.181
skew(dlogY)	0.176	0.208	0.146	0.165	0.169
scorr(π/Y)	0.599	0.608	0.590	0.596	0.600
scorr(log(Y/Khat))	0.838	0.849	0.834	0.837	0.835
scorr(I/K)	0.243	0.200	0.274	0.202	0.297
scorr(ΔlogY)	0.053	0.026	0.073	0.015	0.099
bcorr(π/Y, log(Y/Khat))	-0.271	-0.280	-0.275	-0.270	-0.259
OI/100	183	208	179	215	157

Table A.4: Robustness Tests – Continued

Parameters	(1) benchmark	(6) type-5	(7) $\sigma_\mu > 0$	(8) $\sigma_\sigma > 0$	(9) $\sigma_{meI} > 0$
σ_τ	0.714	0.690	0.721	0.712	0.745
$\mu_{log\alpha}$	-2.606	-2.620	-2.604	-2.592	-2.654
$\sigma_{log\alpha}$	0.557	0.557	0.551	0.556	0.577
$\mu_{log\eta}$	-2.808	-2.851	-2.805	-2.805	-2.776
$\sigma_{log\eta}$	0.725	0.692	0.728	0.719	0.716
b^q	0.278	0.284	0.325	0.308	0.405
b^i	0.000	0.001	0.000	0.000	0.479
b^f	0.034	0.034	0.039	0.031	0.059
μ	0.080	0.082	0.083	0.080	0.061
σ	0.425	0.424	0.411	0.403	0.465
σ_{meK}	0.401	0.402	0.404	0.390	..
σ_{meY}	0.001	0.000	0.002	0.001	0.001
$\sigma_{me\pi}$	0.578	0.597	0.576	0.575	0.561
σ_μ	..	..	0.080	..	..
σ_σ	..	..	..	0.151	..
σ_{meI}	..	..	..	..	0.114
Moments					
mean(π/Y)	0.154	0.148	0.154	0.155	0.153
mean(log(Y/Khat))	1.146	1.155	1.154	1.147	1.104
mean(I/K)	0.173	0.175	0.177	0.171	0.135
mean(ΔlogY)	0.080	0.082	0.083	0.080	0.060
bsd(π/Y)	0.075	0.071	0.074	0.074	0.075
wsd(π/Y)	0.049	0.048	0.048	0.049	0.047
bsd(log(Y/Khat))	0.878	0.880	0.883	0.875	0.870
wsd(log(Y/Khat))	0.332	0.331	0.334	0.324	0.144
bsd(I/K)	0.164	0.165	0.180	0.161	0.135
wsd(I/K)	0.215	0.214	0.213	0.213	0.169
bsd(ΔlogY)	0.163	0.163	0.168	0.162	0.165
wsd(ΔlogY)	0.219	0.217	0.210	0.218	0.230
skew(π/Y)	0.854	1.010	0.852	0.846	0.846
skew(log(Y/Khat))	0.004	0.013	0.004	0.006	0.029
skew(I/K)	2.251	2.193	2.225	2.295	2.412
skew(dlogY)	0.176	0.176	0.195	0.157	0.268
scorr(π/Y)	0.599	0.581	0.604	0.598	0.620
scorr(log(Y/Khat))	0.838	0.839	0.838	0.844	0.976
scorr(I/K)	0.243	0.250	0.292	0.237	0.268
scorr(ΔlogY)	0.053	0.058	0.103	0.051	0.021
bcorr(π/Y, log(Y/Khat))	-0.271	-0.319	-0.263	-0.274	-0.299
OI/100	183	229	148	179	741

Table A.5: Specification Tests

	col (1) benchmark	col (2) $\sigma_{log\alpha}$=$\sigma_{log\eta}$=0	col (3) b^q=b^i=b^f=0	col (4) σ_{meK}=σ_{meY}=$\sigma_{me\pi}$=0
Parameters				
σ_τ	0.714	0.924	0.665	0.734
$\mu_{log\alpha}$	-2.606	-2.351	-2.645	-2.742
$\sigma_{log\alpha}$	0.557	**0.000**	0.587	0.500
$\mu_{log\eta}$	-2.808	-2.494	-2.716	-2.998
$\sigma_{log\eta}$	0.725	**0.000**	0.660	0.885
b^q	0.278	0.443	**0.000**	0.163
b^i	0.000	0.000	**0.000**	0.476
b^f	0.034	0.082	**0.000**	0.041
μ	0.080	0.078	0.100	0.054
σ	0.425	0.354	0.205	0.443
σ_{meK}	0.401	0.380	0.420	**0.000**
σ_{meY}	0.001	0.123	0.110	**0.000**
$\sigma_{me\pi}$	0.578	0.816	0.541	**0.000**
Moments				
mean(π/Y)	0.154	0.171	0.155	0.141
mean(log(Y/Khat))	1.146	1.011	1.151	1.218
mean(I/K)	0.173	0.168	0.206	0.127
mean(ΔlogY)	0.080	0.078	0.100	0.053
bsd(π/Y)	0.075	0.042	0.073	0.071
wsd(π/Y)	0.049	0.073	0.047	0.000
bsd(log(Y/Khat))	0.878	0.848	0.872	0.851
wsd(log(Y/Khat))	0.332	0.328	0.343	0.137
bsd(I/K)	0.164	0.146	0.145	0.136
wsd(I/K)	0.215	0.218	0.274	0.177
bsd(ΔlogY)	0.163	0.153	0.123	0.160
wsd(ΔlogY)	0.219	0.254	0.227	0.221
skew(π/Y)	0.854	0.184	0.887	0.391
skew(log(Y/Khat))	0.004	0.008	0.011	0.013
skew(I/K)	2.251	2.220	1.586	2.450
skew(dlogY)	0.176	0.213	0.002	0.370
scorr(π/Y)	0.599	-0.001	0.604	1.000
scorr(log(Y/Khat))	0.838	0.830	0.822	0.977
scorr(I/K)	0.243	0.126	-0.047	0.242
scorr(ΔlogY)	0.053	-0.149	-0.223	0.027
bcorr(π/Y, log(Y/Khat))	-0.271	-0.019	-0.304	-0.208
OI/100	183	1510	653	3127