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Investment-cash flow sensitivities and capital misallocation

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ABSTRACT

This paper directly estimates the effect of financing constraint on capital misallocation. We provide a simple theoretical framework that links the heterogeneity in investment-cash flow sensitivity, a common indicator of financing constraint, to the dispersion of marginal revenue product of capital, a direct measure of allocative inefficiency. Our model shows that the existence of both constrained and unconstrained firms is a sufficient though not necessary condition for capital misallocation. Empirically, we run an error-correction investment model for U.S. Compustat and Chinese manufacturing firms, and for various sub-samples of the Chinese firms. Our estimates on investment-cash flow sensitivities imply a 5% and 15% total factor productivity loss respectively for the balanced and unbalanced panels of Chinese firms. Our identification strategy does not require any monotonic relationship between investment-cash flow sensitivities and severity of financial frictions, thus is not subject to the Kaplan and Zingales critique.

1. Introduction

Inputs misallocation across heterogeneous production units lowers aggregate total factor productivity (TFP). A new and growing literature, as surveyed in Restuccia and Rogerson (2013), finds that difference in allocative efficiency may be an important explanation to the large and persistent cross-country income differences. Among various sources of misallocation, perhaps the single most studied mechanism is through financial frictions.

Quantifying how much the observed capital misallocation can be accounted for by financial frictions is the central theme of a recent literature.[1] While modelling details and estimated magnitudes differ, these studies share a common methodology: they develop theoretical models and gauge the size of TFP loss, by calibrating model parameters to match the distribution and dynamics of output across production units. In this paper, we propose an alternative accounting framework to estimate TFP loss due to financial frictions, using investment-cash flow sensitivity.

Investment-cash flow sensitivity arises from a large body of empirical literature, which aims to test the presence of financial frictions. Following Fazzari et al. (1988), this literature adds a cash flow variable to a standard Q model of investment, and investigates the sensitivity of investment to cash flow across different sub-samples of firms. A common finding is that there is a stronger correlation between investment and cash flow for sub-samples that are considered more likely to face financing constraint. This finding has often been cited as evidence of significant capital market imperfections.

Though investment-cash flow sensitivity is frequently used as an indicator of financing constraint, and financing constraint is one of the major sources of capital misallocation, there has not been any research, to our knowledge, that connects capital misallocation directly to investment-cash flow sensitivity. This paper attempts to fill in this gap by providing a simple yet consequential theoretical model, which links the heterogeneity in investment-cash flow sensitivity, a common indicator of financing constraint, to the dispersion of marginal revenue product of capital (MRPK), a direct measure of allocative inefficiency. We then apply this accounting framework to a panel of Chinese manufacturing firms and calculate the aggregate TFP loss implied by the investment-cash flow sensitivities estimated from various sub-samples.

The validity of this new approach, of course, depends crucially on the answers to two methodological questions. First, whether investment-cash flow sensitivity is a reliable indicator of financing con-

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[1] For example, Jeong and Townsend (2007), Banerjee and Moll (2010), Amaral and Quintin (2010), Greenwood et al. (2010), Buera et al. (2011), Cole et al. (2016), in addition to those papers we discuss below in detail.

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straint. Even under perfect capital markets, cash flow sensitivity may result from measurement errors in Tobin's Q (Ericson and Whited, 2000), or from imperfect competition and/or decreasing return to scale (Cooper and Ejarque, 2003), or from the presence of capital adjustment costs (Pratap, 2003), or a combination of measurement error in Q and identification problems (Gomes, 2001). Furthermore, a firm's cash flow position is endogenous to its productivity shocks and may contain information about its investment opportunities (Hennessy and Whited, 2007).

To address these concerns, we present a structural model of costly external finance. Firms in this model are allowed to face imperfect competition and/or use decreasing returns to scale technology. In the absence of any friction, our model generates the same optimal condition as those models in the recent literature: optimal capital stock is only a function of current output, Jorgensonian user cost of capital and production technology. This allows us to develop an empirical specification for investment that does not rely on Tobin's Q. We then consider an autoregressive-distributed lag structure to accommodate the possibility of capital adjustment costs, which yields an error-correction specification as in Bond et al. (2003). Under the null hypothesis of no financial frictions, cash flow should not affect investment under this specification. We allow for the potential endogeneity of cash flow in our estimation using GMM techniques. And we test whether the cash flow terms show significantly different predicting powers across those samples that produce significantly different investment-cash flow sensitivities.

The second concern regarding investment-cash flow sensitivity and financing constraint is the well-known Kaplan and Zingales critiques.[2] Kaplan and Zingales (1997) argue that investment-cash flow sensitivities do not always monotonically increase as firms become more financially constrained. Thus one cannot in general use estimates of investment-cash flow sensitivities to proxy the severity of financial frictions. Our theoretical model shows that the relationship between investment-cash flow sensitivities and the severity of financial frictions indeed depends on the curvature of the profit function and the cost function of external finance. However, even though more-financially-constrained firms do not necessarily exhibit higher sensitivity, it remains the case that unconstrained firms should display no investment-cash flow sensitivity. Therefore, finding that one group of firms has positively significant sensitivity while the other group shows no sensitivity is a sufficient though not necessary condition of capital misallocation, which is indeed the general pattern of our empirical finding. Given that our identification strategy only relies on investment-cash flow sensitivities instead of excess investment-cash flow sensitivities, it is not subject to the Kaplan and Zingales critique.

By proposing an alternative approach and providing another set of estimates, this paper is closely related and contributes to the current literature, which addresses the ongoing debate regarding the importance of financial frictions on aggregate TFP. On the one hand, there is a large literature, such as Buera and Shin (2013) and Caselli and Gennaioli (2013), that simulates a substantial TFP loss from various models of financial frictions. On the other hand, Midrigan and Xu (2014) find that a collateral constraint model consistent with Korean plant-level data only implies a fairly small loss, where the key mechanism that undoes the capital misallocation is self-financing. Using firm-specific borrowing costs for U.S. manufacturing firms directly from the interest rate spreads on their outstanding publicly-traded debt, Gilchrist et al. (2013) also find a very modest loss. More recently, the literature has pointed out two important reasons that may drive the wide range of the effects: the persistence of the productivity shocks (Buera and Shin, 2011; Moll, 2014); and whether the effect is on transition dynamics or steady state (Jeong and Townsend, 2007; Buera and Shin, 2013; Moll, 2014).

[2] A recent discussion and evaluation on the Kaplan and Zingales critiques can be found in Bond and Söderbom (2013).

According to our accounting framework, the observed MRPK is a function of both investment-cash flow sensitivities and firm's optimal choice on capital stock and external finance. This implies that we do not have to directly calibrate the persistence of the productivity shocks, or any other model parameters. Neither do we have to take a pre-assumption on whether the firms are at the steady state. Instead, we take a snap shot of the firms in our sample and ask how large the efficiency loss is, according to their actual investment and financing behavior. On this regard, we share the same spirit as Gilchrist et al. (2013). That is we directly make use of the observed firm behavior, which is the outcome of both financial frictions and firm's optimal response.

The findings of the paper are as follows. When we apply the error-correction investment model to a 10-year balanced panel of U.S. Compustat firms, we do not detect any investment-cash flow sensitivity. In contrast, there are significant sensitivities for a 10-year balanced panel made of Chinese firms. Within Chinese firms, when splitting the sample using any criterion based on age, size, ownership or political connection, and both for the balanced and unbalanced panels, we obtain significant cash flow effects for those that are young, small, non-state-owned and without political connection. The resulting aggregate TFP loss implied by these investment-cash flow sensitivities are 4.0–5.2% for the balanced panel and 10.0–15.2% for the unbalanced panel.

The rest of this paper is organized as follows. Section 2 provides a theoretical framework mapping the investment-cash flow sensitivities to MRPK. Section 3 describes the empirical specification used to estimate investment-cash flow sensitivities. Section 4 presents our estimates on investment-cash flow sensitivities and calculates the implied aggregate TFP loss due to financing constraint. Section 5 concludes.

2. Model

2.1. The production environment

Firm i receives an investment opportunity represented by a stochastic productivity parameter Z_i. It makes an investment I_i to build up capital stock $K_i = (1-\delta)K_{i,-1} + I_i$, where δ is the depreciation rate and $K_{i,-1}$ is its lagged capital stock. The firm employs capital K_i and variable inputs L_i to produce output Y_i according to a production technology,

$$Y_i = Z_i^{1-\eta}\left(K_i^{\alpha} L_i^{1-\alpha}\right)^{\eta},$$

where $0 < \eta < 1$ is the degree of returns to scale.[3]

Denote w as the wage rate. For a given capital stock K_i, firm i chooses variable inputs L_i to maximize its instantaneous gross profit:

$$\pi_i = \max_{L_i} \{Y_i - wL_i\}.$$

The solved-out profit function is given by

$$\pi(Z_i, K_i) = Z_i^{\gamma} K_i^{1-\gamma}, \tag{1}$$

where

$$\gamma \equiv \frac{1-\eta}{1-\eta+\alpha\eta}. \tag{2}$$

The first-order condition for optimal choice of variable inputs yields

$$\frac{wL_i}{Y_i} = (1-\alpha)\eta,$$

which implies that the gross profit is always a constant share of output in this model,

$$\frac{\pi_i}{Y_i} = 1 - \eta + \alpha\eta. \tag{3}$$

[3] Decreasing returns to scale may be due to managerial technology (where η is the Lucas span-of-control parameter), or due to Dixit-Stiglitz type of monopolistic competition in an environment with heterogenous products (where $1-\eta$ is the inverse of the demand elasticity).

2.2. A model of costly external finance

Since the purpose of our analysis is not to identify the source of financial frictions, but rather to understand the effects of financial frictions on investment and capital misallocation, we consider a very simple but highly synthesized model of financing constraints. Stein (2003) demonstrates that this reduced-form model can be mapped precisely into a variant of the Townsend (1979) costly state verification model; and a re-parameterized Myers and Majluf (1984) adverse selection model can lead to essentially the same reduced form. Asymmetric information, and in particular costly state verification, is the micro foundation of a large group of macro literature on financial frictions.[4] The model itself is static in nature. A dynamic extension can be found in Wu (2018), which yields the same implications of financing constraint on capital misallocation. Our empirical exercises also accommodate possible dynamics arising from capital adjustment costs using an error-correction specification.

Of the investment I_i, an amount W_i is financed out of internal funds and an amount D_i is raised externally, via issues of new debt, equity or other financial claims. Thus the budget constraint is $D_i = I_i - W_i$. Assume that there are deadweight costs associated with funds raised externally. These costs are given by $\theta_i C(D_i)$, where $C(D_i)$ is a convex function, and θ_i measures the degree of financial frictions faced by firm i. The firm chooses an optimal investment to maximize the firm value:

$$\max_{I_i} \frac{\pi(Z_i, K_i)}{1+r} - I_i - \theta_i C(D_i) \tag{4}$$

where r is the interest rate. The first-order condition implies setting the marginal revenue product of capital equal to the user cost of capital (UCC):

$$MRPK_i \equiv \pi_K(Z_i, K_i) = (1+r)\left[1 + \theta_i C_D(D_i)\right] \equiv UCC_i \tag{5}$$

Differentiating Equation (5) with respect to W_i, and rearranging the result, we get:

$$\theta_i = \frac{-\pi_{KK}(Z_i, K_i)}{(1+r)\, C_{DD}(D_i)} \frac{dI_i/dW_i}{(1 - dI_i/dW_i)} \tag{6}$$

where dI_i/dW_i is known as the investment-cash flow sensitivity in the literature, first introduced by Fazzari et al. (1988) as a measure of firm i's degree of financing constraint.

2.3. The immunity to the Kaplan and Zingales critique

Based on some a priori measure, for example, the dividend payout decision, Fazzari et al. (1988) classify firms into constrained and unconstrained groups. And their empirical exercises show that more-constrained firms exhibit higher investment-cash flow sensitivities than less-constrained firms. Fig. 1 illustrates this scenario by assuming that $C(D_i)$ is a quadratic function, so that for two otherwise identical firms A and B, if $dI_A/dW_A > dI_B/dW_B$, one may infer that $\theta_A > \theta_B$.

This finding is opposed by Kaplan and Zingales (1997). They argue that this investment-cash flow sensitivity does not always monotonically increase as firms become more financially constrained. The requirement for this monotonicity involves certain relationships between the production function and the function of cost of external funds. Empirically they find that firms classified as less financially constrained exhibit significantly greater investment-cash flow sensitivities than those firms classified as more financially constrained. Fig. 2 presents such a situation by assuming that $C(D_i)$ is a quadratic function and $\pi_K(Z_i, K_i)$ is sufficiently convex, so that for two otherwise identical firms A and B, one may detect $dI_A/dW_A < dI_B/dW_B$, even though $\theta_A > \theta_B$.

[4] For example, Bernanke and Gertler (1989), Castro et al. (2009), Greenwood et al. (2010, 2013) and Cole et al. (2016).

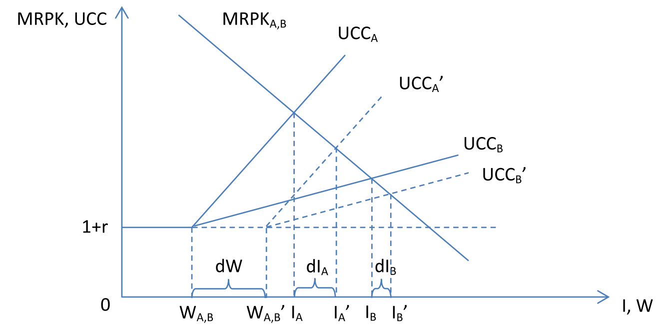

Fig. 1. The scenario of Fazzari et al. (1988).

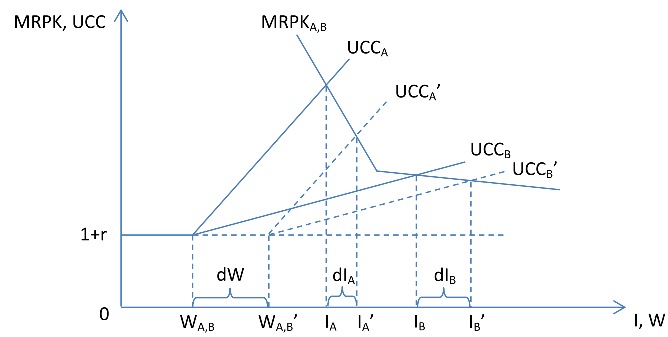

Fig. 2. The scenario of Kaplan and Zingales (1997).

The non-monotonicity between investment-cash flow sensitivities (dI_i/dW_i) and measures of financial frictions (θ_i) is known as the Kaplan and Zingales critique. Our paper, however, is not subject to this critique. This is because the Kaplan and Zingales critique applies to the excess investment-cash flow sensitivities when inferring financial frictions for groups of firms that are all constrained. In contrast our paper investigates a different condition where only one group of firms are found constrained. Although it is not necessarily true that the magnitude of the sensitivity increases in the degree of financing constraint, it is true that constrained firms should be sensitive to internal funds while unconstrained firms should not. This property can be illustrated in Fig. 3, where we still assume $C(D_i)$ is a quadratic function and allow $\pi_K(Z_i, K_i)$ to have any degree of convexity. Under this scenario, we do not rely on the condition $dI_A/dW_A > dI_B/dW_B$ to infer that $\theta_A > \theta_B$. Instead, our empirical findings can be summarized as $dI_A/dW_A > 0$ and $dI_B/dW_B = 0$, which must imply that $\theta_A > 0$ and $\theta_B = 0$.

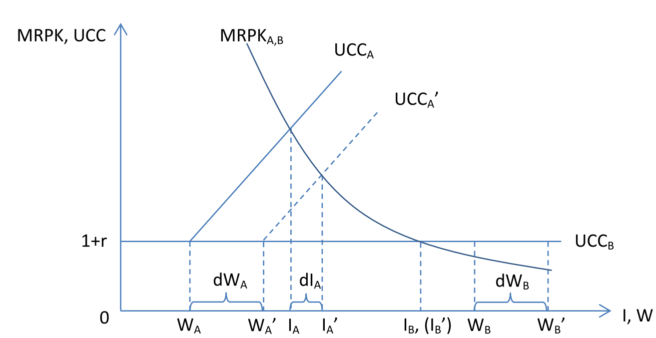

Fig. 3. The scenario of our empirical findings.

2.4. Financing constraint, capital misallocation and aggregate TFP loss

By substituting Equation (6) back to Equation (5), we get:

$$MRPK_i = (1+r)\left[1 - \frac{\pi_{KK}(Z_i, K_i)C_D(D_i)}{(1+r)C_{DD}(D_i)}\frac{dI_i/dW_i}{(1-dI_i/dW_i)}\right] \quad (7)$$

Our investment model thus illustrates an intuitive mechanism on how financing constraint may cause capital misallocation, by providing a link between the heterogeneity in investment-cash flow sensitivity, dI_i/dW_i, a common indicator of financing constraint, and the dispersion of marginal revenue product of capital, $MRPK_i$, a direct measure of allocative inefficiency.

When both Z_i and $MRPK_i$ are log-normally distributed, the aggregate TFP loss caused by capital misallocation can be approximated as:

$$\Delta \ln TFP = \frac{\alpha\eta\,[1-\eta+\alpha\eta]}{2(1-\eta)}\mathrm{var}\,(\ln MRPK_i) \quad (8)$$

If we assume a quadratic cost function $C(D) = \frac{1}{2}D^2$, in addition to the functional form assumption on profit $\pi(Z_i, K_i) = Z_i^{\gamma}K_i^{1-\gamma}$, Equations (7) and (8) then map the aggregate TFP loss into the dispersion of firm's profitability, debt ratio and investment-cash flow sensitivities:

$$\Delta \ln TFP = \frac{\alpha\eta\,[1-\eta+\alpha\eta]}{2(1-\eta)}\mathrm{var}\left[\ln\left(1 + \frac{\gamma(1-\gamma)}{(1+r)}\frac{\pi_i}{K_i}\frac{D_i}{K_i}\frac{dI_i/dW_i}{(1-dI_i/dW_i)}\right)\right] \quad (9)$$

In an economy with heterogeneous firms, if $dI_i/dW_i = 0\ \forall i$, then obviously $MRPK_i = 1 + r\ \forall i$; therefore, there would be no capital misallocation and efficiency loss. When $dI_i/dW_i \neq 0\ \forall i$, the implications of financing constraint on capital misallocation and efficiency loss is less clear. On the one hand, the internal funds W_i is an endogenous state variable in a dynamic setting. Firms facing persistently higher financial frictions will optimally accumulate more internal funds due to the precautionary savings motive. Midrigan and Xu (2014) show that at the steady state this self-financing mechanism will undo the capital misallocation and imply a fairly small efficiency loss. On the other hand, Moll (2014) demonstrates that even at the steady state, the persistence of idiosyncratic productivity shocks Z_i determines both the size of steady state efficiency loss and the speed of transitions: if shocks are persistent, the steady state loss is small but transitions are slow. Even if financial frictions are unimportant in the long run, they tend to matter in the short run. If shocks are less persistent, transitions will be fast but the steady state loss will be large. Thus financial frictions could be important even in the long run.

In this paper, we do not directly test whether the productivity shocks are persistent or not. Neither do we have to take a pre-assumption on whether the firms are at the steady state or not. Instead, we take a snap shot of the firms in our sample and ask how large the efficiency loss is, according to their actual investment and financing behavior.

Our accounting framework makes use of an important fact that the observed MRPK, as highlighted by Equation (9), is a function of both investment-cash flow sensitivities and firm's optimal choice on capital stock and external finance, for given productivity shocks and financial frictions. There are two important properties associated with this fact. First, as found in most cases of our sample-splitting tests, when $dI_i/dW_i > 0\ \forall i \in A$ and $dI_i/dW_i = 0\ \forall i \in B$, it is clear that $MRPK_A > 1 + r$ and $MRPK_B = 1 + r$. Then there must be a dispersion in the MRPK across firms, and hence, capital misallocation exists. Thus the existence of both constrained and unconstrained firms is a sufficient though not necessary condition for capital misallocation.

Second, the size of efficiency loss, our ultimate quantity of interest, also depends on firm's actual investment and financing behavior, which are the outcomes of both financial frictions and firm's optimal response. For example, an over-accumulation of capital stock, could serve as a self-financing mechanism to mitigate the effect of financing constraint. As for to what extent, such mechanism could undo capital misallocation, it is an empirical question. The purpose of the paper is to discipline the aggregate TFP loss in the Chinese manufacturing sector due to financing constraint, by estimating the investment-cash flow sensitivities and employing the observed investment and financing behavior.

3. Empirical specification

3.1. An error-correction model

The error-correction model was first introduced into the investment literature by Bean (1981) and has been applied to test investment-cash flow sensitivities in Bond et al. (2003) and many followers. The basic idea is to nest a long-run specification for the firm's demand for capital within a regression model that allows a flexible specification for short-run investment dynamics to be estimated from the data.

To derive an empirical specification for testing investment-cash flow sensitivities, we start with the benchmark case where there is no financial friction and no capital adjustment cost. According to Equation (1)–(3) and (5), in a frictionless world, a firm's optimal level of capital stock is a linear function of output, Jorgensonian user cost of capital and production technology:

$$k_{it} = y_{it} - \log(1+r_t) + \log\alpha_i\eta_i \quad (10)$$

where k_{it} is the natural logarithm of the optimal capital stock of firm i in year t; y_{it} is its log of output; $\log(1+r_t)$ captures the real user cost of capital, which is allowed to be year-specific; and $\log\alpha_i\eta_i$ captures the production technology, which is allowed to be firm-specific.[5]

With additional assumptions – 1. firm's optimal capital stock in the presence of adjustment costs is proportional to its optimal capital stock in the case of no adjustment cost; 2. short-run investment dynamics can be well-approximated by distributed lags in the regression model; 3. the variation in the user cost of capital and production technology can be controlled for by including both year-specific and firm-specific effects – the benchmark model of capital stock can account for the presence of adjustment costs by nesting Equation (10) within a dynamic regression model. Following Bond et al. (2003), if we consider an autoregressive-distributed lag specification with up to second-order dynamics, we have the following ADL(2,2) model:

$$k_{it} = \alpha_1 k_{i,t-1} + \alpha_2 k_{i,t-2} + \beta_0 y_{it} + \beta_1 y_{i,t-1} + \beta_2 y_{i,t-2} + d_t + u_i + v_{it} \quad (11)$$

where d_t is a year dummy, u_i is an unobserved firm-specific effect and v_{it} is an error term. The long-run unit elasticity of capital with respect to output, as can be found in Equation (10), implies that $(\beta_0 + \beta_1 + \beta_2)/(1 - \alpha_1 - \alpha_2) = 1$. Solving for β_2, and substituting into Equation (11) gives

$$\Delta k_{it} = (\alpha_1 - 1)\,\Delta k_{i,t-1} + \beta_0\Delta y_{it} + (\beta_0 + \beta_1)\,\Delta y_{i,t-1} - (1 - \alpha_1 - \alpha_2)\left(k_{i,t-2} - y_{i,t-2}\right) + d_t + u_i + v_{it} \quad (12)$$

We will investigate the validity of this long-run restriction in our empirical analyses. In this specification, we require that the coefficient on the error-correction term $(k_{i,t-2} - y_{i,t-2})$ be negative, so that firms would decrease their investment when actual capital stock is above the optimal level, and vice versa.

Finally, from Equation (12), we derive our main regression model (13) by using the approximation $\Delta k_{it} \approx I_{it}/K_{i,t-1} - \delta_i$, where δ_i denotes the possibly firm-specific depreciation rate, and by including current

[5] Equation (10) can be generalized as $k_{it} = y_{it} - \sigma j_{it} + a_i$, where j_{it} is the log of the real user cost of capital and a_i is the firm-specific intercept. This relationship is in accordance with firm's profit maximization subject to constant returns to scale and a CES production function, and nests the possibility of a fixed capital-output ratio (when $\sigma = 0$). It is also consistent with a Cobb-Douglas production function, with or without constant returns to scale (when $\sigma = 1$).

and lagged cash flow terms $CF_{it}/K_{i,t-1}$ and $CF_{i,t-1}/K_{i,t-2}$ as additional regressors. This yields the following error-correction specification for our empirical analyses:

$$\frac{I_{it}}{K_{i,t-1}} = \rho\frac{I_{i,t-1}}{K_{i,t-2}} + \gamma_0\Delta y_{it} + \gamma_1\Delta y_{i,t-1} + \phi\left(k_{i,t-2} - y_{i,t-2}\right) + \pi_0\frac{CF_{it}}{K_{i,t-1}} + \pi_1\frac{CF_{i,t-1}}{K_{i,t-2}} + d_t + u_i + v_{it} \qquad (13)$$

3.2. Data

The main dataset used in our study is an annual firm-level 10-year balanced panel from the Chinese Industry Survey covering the 1998-2007 period. The survey was conducted by the National Bureau of Statistics of China on a yearly basis. The survey includes all state-owned industrial firms and those non-state-owned industrial firms with sales revenue above RMB 5 millions. These firms account for about 90 percent of the total industrial output in China. There are two companion data sets. The first is an annual firm-level 10-year balanced panel from Standard and Poor's Compustat for U.S. covering the 1998-2007 period. Using these two data sets of China and U.S. simultaneously allows us to compare our empirical findings and implement a set of specification tests. The second is the 10-year unbalanced panel of the Chinese Industry Survey covering the same period. Comparing the results from the balanced and unbalanced panels thus highlights the effects of financial frictions on capital misallocation via the extensive margin.

More details of our data sets such as data construction and variables' definition are given in Appendix A. Table A1 reports the mean values and standard deviations of the variables used in our regression model for the three panels.

3.3. Estimation

Our regression models are estimated using the 'first-differenced' GMM method for dynamic panel data introduced by Arellano and Bond (1991). This method was shown to produce consistent estimates in the presence of firm-specific effects and allow for all the explanatory variables to be potentially endogenous. This is particularly important since the endogeneity of cash flow is one of the major concerns in the literature of investment-cash flow sensitivities.

We start off by considering the time series properties of the variables used in Equation (13). More specifically, we want to see whether or not any of these variables follows random walk. Random-walk properties for any of these variables will cause an unidentification problem for our GMM estimation since it relies on using lagged of these variables as instruments in the differenced equations and since these instruments will become uninformative in the case of random walk.

Table A2 reports the estimation results of simple AR(1) models of I_t/K_{t-1}, Δy, CF_t/K_{t-1}, and $k-y$ using OLS. In any estimated models for both countries, the OLS estimates of the coefficients are found to be significantly below one. To the extent that the OLS estimates in the AR(1) model with fixed effects like these tend to be biased upwards, this result assures us that none of these variables exhibits random walk. Table A2 also reports within-groups and GMM estimators for comparison purposes. Notice that the finding of stationary $k-y$ in our data is consistent with the long-run unit-elasticity of capital with respect to output imposed in our empirical model construction.

The key parameters of interest in Equation (13) are π_0 and π_1. This model has an advantage over the so-called Q model as it avoids using the possibly mismeasured Q in the estimation. However, one needs to be careful with the interpretation of these cash flow coefficients. Under the null hypothesis of no financing constraint, one would expect an insignificant cash flow coefficient. However, although a significant cash flow coefficient could indicate the presence of financial constraints, the coefficient can still be significant even in the absence of financing constraints. This is because cash flow may help predict future investment opportunity, if the other explanatory variables in Equation (13) do not fully control for the investment opportunity due to model misspecification. Under such scenario, cash flow will help to explain investment spending in our regression model, even the firms are not financially constrained.

We rule out this possibility by directly investigating whether lagged cash flow variables forecast future sales growth, a common proxy for investment opportunity, differently across the sub-samples in each sample-splitting test. Table A3 reports the OLS estimates for these forecasting models for the two balanced panels of China and U.S. Although individually the lagged cash flow terms are significant in the model for China, the coefficients are rather small.

The lower panel of Table A3 reports the test statistics for the null hypothesis that the sum of the coefficients on both cash flow terms is zero. We cannot reject the null hypothesis for both China and U.S. at the 1% significance level. The p-value of the test for the U.S. sample is close to the 5% significance level. However, both cash flow terms are individually statistically insignificant, and the sum of the coefficients −0.017 is economically small. This implies that the cash flow terms play little role in the forecasting model for both samples.

We have also conducted the same exercises in all our sample-splitting regressions, and found that the lagged cash flow terms do not systematically vary across our sub-samples under each splitting criterion. These results re-assure us of the reliability of our interpretations on investment-cash flow sensitivities as an indicator of financing constraint.

4. Results

4.1. Estimates on investment-cash flow sensitivities

4.1.1. U.S. and China

Table 1 presents our GMM results for the full sample of the balanced-panel of U.S. and China. The instruments used in these regressions are the lagged values of $I_{it}/K_{i,t-1}, CF_{it}/K_{i,t-1}, \Delta y_{it}, k_{it} - y_{it}$ dated back two periods and further (this will apply to all our GMM estimations, if not stated otherwise). In doing this, we implicitly assume that both current cash flow and sales growth rate are endogenous variables; hence, lag-1 of these variables are not valid instruments. As can be seen, the coefficient on cash flow is highly positively significant for China, while insignificant for U.S., indicating that Chinese firms are financially constrained and U.S. firms are not. This finding is consistent with the evidence from many international comparisons, such as Love (2003), that firms in a less developed financial market are more likely to face financing constraint. The p-values for the m1, m2, and Sargan tests are reported in the middle of the table, which show no indication of invalid instruments or unreliable estimates.[6] The lower panel of Table 1 reports the test statistics for the null hypothesis that the sum of the coefficients on both cash flow terms is zero. In contrast to what we have seen in Table A3, the explanatory power of cash flow terms in the investment model is totally different for China and U.S. Here the null hypothesis is strongly rejected in the China sample but cannot be rejected in the U.S. sample.

The estimates on other coefficients also allow us to back out the structural parameters in Equation (11). For U.S., the short-run dynamics in capital stock can be described as

$$k_{it} = 0.724k_{i,t-1} - 0.134k_{i,t-2} + 0.560y_{it} - 0.202y_{i,t-1} + 0.052y_{i,t-2},$$

while for China this process is captured by

$$k_{it} = 0.964k_{i,t-1} - 0.081k_{i,t-2} + 0.078y_{it} + 0.046y_{i,t-1} - 0.007y_{i,t-2}.$$

[6] The null hypothesis for m1 (m2) test is no first-order (second-order) serial correlation in Δv_{it}. The null hypothesis for Sargan test is the validity of the instruments.

Table 1
Error-Correction Models: First-Differenced GMM, t-2 Instruments.

	China	U.S.
I_{t-1}/K_{t-2}	−0.036	−0.276**
	(0.019)	(0.058)
Δy_t	0.078	0.560**
	(0.052)	(0.085)
Δy_{t-1}	0.124**	0.358**
	(0.021)	(0.075)
$(k-y)_{t-2}$	−0.117**	−0.410**
	(0.022)	(0.074)
CF_t/K_{t-1}	0.402**	−0.047
	(0.103)	(0.055)
CF_{t-1}/K_{t-2}	−0.074*	0.039
	(0.035)	(0.025)
Obs.	55,094	4000
m1	0.000	0.000
m2	0.991	0.845
Sargan	0.065	0.360
Test statistics for H_0		
chi (1)	20.78	0.07
Prob > chi2	0.000	0.786

Note:
1. Two-step Windmeijer robust standard errors are reported in parentheses.
2. Obs. means number of observations used in each regression.
3. We report p-values for m1, m2 and Sargan tests.
4. *Significant at the 5% level; **Significant at the 1% level.
5. H_0: coefficient of CF_tK_{t-1} + coefficient of $CF_{t-1}/K_{t-2} = 0$.

Table 2
Error-Correction Models: Age, First-Differenced GMM, t-2 Instruments.

	China		U.S.	
	Young	Old	Young	Old
I_{t-1}/K_{t-2}	−0.056*	−0.065*	−0.370**	−0.218**
	(0.024)	(0.027)	(0.085)	(0.062)
Δy_t	0.097	0.169**	0.562**	0.597**
	(0.058)	(0.062)	(0.100)	(0.086)
Δy_{t-1}	0.152**	0.122**	0.532**	0.234**
	(0.027)	(0.033)	(0.093)	(0.084)
$(k-y)_{t-2}$	−0.134**	−0.139**	−0.561**	−0.295**
	(0.028)	(0.033)	(0.102)	(0.085)
CF_t/K_{t-1}	0.307**	0.200	−0.062	−0.033
	(0.110)	(0.113)	(0.047)	(0.067)
CF_{t-1}/K_{t-2}	−0.025	−0.076	0.015	0.081
	(0.038)	(0.048)	(0.023)	(0.046)
Obs.	29,560	25,534	1909	2091
m1	0.000	0.000	0.000	0.000
m2	0.581	0.233	0.728	0.542
Sargan	0.038	0.263	0.389	0.606

Note:
1. Two-step Windmeijer robust standard errors are reported in parentheses.
2. Obs. means number of observations used in each regression.
3. We report p-values for m1, m2 and Sargan tests.
4. *Significant at the 5% level; **Significant at the 1% level.

The comparison indicates that capital stock in China is much more dependent on its lagged level and responds much less to current output than that in U.S. As highlighted in Equation (10), in a frictionless world, capital stock would not rely on its historical level and should have a unit elasticity with respect to current output. This implies that these Chinese firms might face more substantial capital adjustment costs than the U.S. firms.

Table 3
Error-Correction Models: Size, First-Differenced GMM, t-2 Instruments.

	China		U.S.	
	Small	Large	Small	Large
I_{t-1}/K_{t-2}	−0.031	−0.113**	−0.210**	−0.438**
	(0.027)	(0.025)	(0.061)	(0.065)
Δy_t	0.119*	0.161**	0.506**	0.589**
	(0.060)	(0.061)	(0.098)	(0.090)
Δy_{t-1}	0.103**	0.196**	0.323**	0.521**
	(0.032)	(0.030)	(0.074)	(0.086)
$(k-y)_{t-2}$	−0.102**	−0.186**	−0.332**	−0.616**
	(0.033)	(0.030)	(0.068)	(0.083)
CF_t/K_{t-1}	0.492**	0.061	0.018	−0.119*
	(0.130)	(0.111)	(0.038)	(0.059)
CF_{t-1}/K_{t-2}	−0.075*	0.060	0.0200	0.048
	(0.038)	(0.047)	(0.024)	(0.036)
Obs.	26,472	28,622	1917	2083
m1	0.000	0.000	0.000	0.000
m2	0.949	0.953	0.993	0.972
Sargan	0.185	0.272	0.499	0.266

Note:
1. Two-step Windmeijer robust standard errors are reported in parentheses.
2. Obs. means number of observations used in each regression.
3. We report p-values for m1, m2 and Sargan tests.
4. *Significant at the 5% level; **Significant at the 1% level.

Table 4
Error-Correction Models: China, Ownership and Union, First-Differenced GMM, t-2 Instruments.

	Ownership		Labor Union	
	Non-SOEs	SOEs	Non-Union	Union
I_{t-1}/K_{t-2}	−0.041*	−0.149*	−0.053	−0.060**
	(0.019)	(0.060)	(0.032)	(0.021)
Δy_t	0.101*	0.078	0.041	0.152**
	(0.053)	(0.057)	(0.063)	(0.054)
Δy_{t-1}	0.127**	0.176*	0.164**	0.134**
	(0.021)	(0.070)	(0.037)	(0.024)
$(k-y)_{t-2}$	−0.120**	−0.196**	−0.147**	−0.133**
	(0.022)	(0.071)	(0.038)	(0.025)
CF_t/K_{t-1}	0.356**	0.011	0.437**	0.272**
	(0.101)	(0.096)	(0.121)	(0.105)
CF_{t-1}/K_{t-2}	−0.059	−0.001	−0.043	−0.044
	(0.035)	(0.047)	(0.047)	(0.039)
Obs.	51,929	3165	15,414	39,680
m1	0.000	0.000	0.000	0.000
m2	0.744	0.119	0.960	0.774
Sargan	0.072	0.705	0.139	0.141

Note:
1. Two-step Windmeijer robust standard errors are reported in parentheses.
2. Obs. means number of observations used in each regression.
3. We report p-values for m1, m2 and Sargan tests.
4. *Significant at the 5% level; **Significant at the 1% level.

4.1.2. Age and size

We now further investigate the degree of financing constraints of different types of firms within U.S. and China, based on two criteria widely used in the literature: age and size.

For sample splitting based on age, we classify firms into two categories: young and old. A firm is regarded as young (old) firm in a specific year if its age is below (above) the median age in the annual age distribution of all firms. Table 2 reports the results based on age-splitting for China and U.S. respectively. As indicated in the right panel, young firms in China exhibit a significant cash flow sensitivity while the old firms do not show such significance, implying that we cannot reject the null hypothesis that young Chinese firms in our sample are financially constrained. In contrast, in the right panel we find that both young and old firms in the U.S. show insignificant investment-cash flow sensitivities. This result is not insensible, due to the fact that U.S. has a very developed financial market and our U.S. sample consists of only

Table 5
Error-Correction Models: China, Unbalanced panel, First-Differenced GMM, t-2 Instruments.

	Age		Size		Ownership		Labor Union	
	Young	Old	Small	Large	Non-SOEs	SOEs	Non-Union	Union
I_{t-1}/K_{t-2}	−0.064**	−0.052**	−0.042**	−0.080**	−0.064**	−0.034	−0.069**	−0.066**
	(0.016)	(0.013)	(0.015)	(0.015)	(0.011)	(0.035)	(0.015)	(0.014)
Δy_t	0.116*	0.106*	−0.070	0.357**	0.261**	−0.118	0.152	0.244**
	(0.051)	(0.048)	(0.054)	(0.057)	(0.049)	(0.100)	(0.085)	(0.044)
Δy_{t-1}	0.199**	0.162**	0.158**	0.193**	0.187**	0.055	0.217**	0.168**
	(0.020)	(0.017)	(0.021)	(0.018)	(0.013)	(0.056)	(0.020)	(0.018)
$(k-y)_{t-2}$	−0.178**	−0.157**	−0.156**	−0.179**	−0.172**	−0.064	−0.200**	−0.155**
	(0.020)	(0.017)	(0.021)	(0.017)	(0.013)	(0.054)	(0.020)	(0.017)
CF_t/K_{t-1}	0.283*	0.209	0.381**	0.101	0.223*	0.035	0.227	0.067
	(0.141)	(0.128)	(0.134)	(0.150)	(0.105)	(0.160)	(0.155)	(0.132)
CF_{t-1}/K_{t-2}	−0.025	−0.044	−0.082*	0.022	−0.028	0.006	−0.026	0.007
	(0.044)	(0.037)	(0.035)	(0.048)	(0.031)	(0.082)	(0.046)	(0.040)
Obs.	171,350	231,965	164,353	238,962	377,566	25,749	155,248	186,703
m1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
m2	0.514	0.937	0.555	0.631	0.985	0.885	0.238	0.510
Sargan	0.008	0.000	0.006	0.000	0.000	0.490	0.005	0.000

Note:
1. Two-step Windmeijer robust standard errors are reported in parentheses.
2. Obs. means number of observations used in each regression.
3. We report p-values for m1, m2 and Sargan tests.
4. *Significant at the 5% level; **Significant at the 1% level.

Table 6
TFP loss from financing constraint in China.

	CF/K coef	Median ln(Y/K)	Median π/K	Median D/K	TFP Loss
Young	0.307**	0.98	0.45	1.25	3.99%
Old	0.200	0.40	0.27	0.89	
Small	0.492**	0.95	0.40	1.04	5.24%
Large	0.061	0.48	0.31	1.05	
Non-SOEs	0.356**	0.78	0.37	1.07	4.97%
SOEs	0.011	−0.27	0.15	0.76	
Non-Union	0.437**	0.99	0.41	1.12	5.06%
Union	0.272**	0.60	0.33	1.02	

publicly listed firms lasting for at least 10 consecutive years from 1998 to 2007.

Similar sample-splitting tests based on size are presented in Table 3. We classify a firm as small (large) if its asset is below (above) the median asset in the annual asset distribution of all firms. The results exhibit the same pattern as the ones for age. Small firms are found to be constrained while large firms are not for China; both small and large firms are unconstrained for U.S. Thus, our empirical findings that young and small firms are more likely to be financially constrained are consistent with the well-established results in the financing constraint literature, such as Hadlock and Piece (2010), among many others.

4.1.3. Ownership and political connection

Some unique institutional features also allow us to conduct further sample-splitting tests for China. As well-described in Song et al. (2011), capital misallocation in China arises when financially integrated firms have perfect access to the capital market while the entrepreneurial firms are financially constrained. Two firm characteristics have often been used to proxy whether a firm is financially integrated in China: firm ownership and political connection.

We classify firms as SOEs (state-owned enterprises) and non-SOEs (other types of firms), using information on 'ownership code' provided in our Chinese data set. Results based on this ownership splitting are reported in the left panel of Table 4. On the one hand, the cash flow coefficient in SOEs is almost zero, implying this type of firms do not experience any financing constraint. On the other hand, non-SOEs have a highly significant cash flow coefficient of 0.356, reflecting a severe financing constraint they are facing. Thus the heterogeneity in our investment-cash flow sensitivity estimates echoes a well-established finding on financing constraints in China, for example, Dollar and Wei (2007), Hsieh and Klenow (2009), Guariglia et al. (2011) and Brandt et al. (2013).

Whether the head of a firm is a Communist Party member is usually adopted as a measure for political connection in China (Li et al., 2008; Guo et al., 2014). Firms with government-appointed or government-connected chief executive officers are found to face much less severe financial frictions (Fan et al., 2007; Cull et al., 2015). Since there is no information regarding the entrepreneur or chief executive officer in our dataset, we use whether the firm has a labor union as an alternative measure of political connection.[7]

The right panel of Table 4 reports the sample-splitting tests. Even though both union and non-union firms exhibit significant cash flow sensitivities, the latter exhibits a larger magnitude of sensitivity. The results indicate that both union and non-union firms are constrained;

[7] Different from the labor unions in most western countries, which help workers to collectively bargain higher wages and better working conditions with the firms, a labor union in China passes on the ideology of the Communist Party to the workers and watches out whether the firm is politically correct or at least consistent with the Communist Party. Since the Chinese data set covers information on whether or not a firm has a labor union only in the census year 2004, we assume that the firm has a labor union across all our sample period 1998-2007 if it does in 2004.

Table 7
TFP loss from financing constraint in China (unbalanced panel).

	CF/K coef	Median ln(Y/K)	Median π/K	Median D/K	TFP Loss
Young	0.283*	1.43	0.58	1.46	14.51%
Old	0.209	0.83	0.34	1.04	
Small	0.381**	1.55	0.61	1.25	15.15%
Large	0.101	0.78	0.35	1.24	
Non-SOEs	0.223*	1.28	0.51	1.30	12.37%
SOEs	0.035	−0.49	0.10	0.83	
Non-Union	0.227	1.48	0.58	1.44	10.02%
Union	0.067	1.00	0.42	1.22	

nevertheless, non-union firms are more constrained than union firms, subject to the Kaplan-Zingales critique. One might argue that our findings of lower investment-cash flow sensitivities among union firms is simply driven by the existence of more SOEs among union firms compared to non-union firms. To control for this possibility, we apply the same sample-splitting tests among non-SOEs only. Again, we see that non-SOEs union firms exhibit lower sensitivities than their counterparts.

4.1.4. Unbalanced panel

Table 5 presents the results when we apply the sample-splitting tests to the unbalanced panel of the Chinese firms. The cash-flow coefficients are positive and statistically significant only for the young, small and non-SOEs sub-samples in contrast to the old, large and SOEs counterparts. The results for the labor union tests are less clear: while non-union firms do have a larger cash-flow coefficient than that of the union firms, neither of them is statistically significant. This implies that very similar patterns which we have found from the balanced panel remain to be true in the unbalanced panel, although the unbalanced panel has naturally accommodated entry and exit.[8]

4.2. Quantifying aggregate TFP loss

Our sample-splitting tests thus establish a general pattern on the investment-cash flow sensitivities for Chinese firms. That is $dI_i/dW_i > 0\ \forall i \in$ (young, small, non-SOEs) and $dI_i/dW_i = 0\ \forall i \in$ (old, large, SOEs) so that $MRPK_A > 1 + r$ and $MRPK_B = 1 + r$, a sufficient though not necessary condition for capital misallocation.

To quantify the aggregate TFP loss according to equation (9), we use gross-profit-to-capital ratio to proxy π_i/K_i and total-liabilities-to-capital ratio to proxy D_i/K_i. Table 6 presents the median values for these two ratios for the balanced panel of Chinese firms across sub-samples by each criterion of our sample-splitting tests. One interesting finding is that the profitability of the constrained firms is higher than the unconstrained firms under each of the splitting criterion; while the differences in debt ratio are evident only when we split the sample by age and ownership. Recall that both the profitability and debt ratio are the firm's optimal response for given productivity shocks and financial frictions.

We also list the output-to-capital ratio $\ln(Y_i/K_i)$ and the estimated cash-flow coefficients. It is evident that young, small, non-SOEs and non-union firms, which generate positive and significant cash-flow coefficients, have much higher output-to-capital ratios than the old, large, SOEs and union firms. Thus there is indeed a dispersion of output-to-capital ratio, a commonly-watched indicator of capital misallocation pioneered by Hsieh and Klenow (2009), across firms when we split the sample using any criterion based on age, size, ownership or political connection.

Assuming $\alpha = 1/3, \eta = 0.85$, and $r = 0.10$, we can now calculate the TFP loss using our framework (9). The choice of α and η is standard and strictly follows the literature, such as Midrigan and Xu (2014) and Gilchrist et al. (2013). The choice of r varies more in the literature. Here we have a 5% risk-free interest rate and a 5% risk premium in mind. All else being equal, a lower r will lead to a higher TFP loss. Under these benchmark parameter values, the resulting TFP loss is $3.99\%, 5.24\%, 4.97\%$ and 5.06% respectively, when we employ the investment-cash flow sensitivities generated from the 10-year balanced panel for China, using age, size, ownership and political connection as the splitting criterion. The fact that the estimated aggregate TFP loss falls into a tight range when we use any of the splitting criterion is reassuring.

To see whether the estimated loss is sensitive to the choice of parameter values, we perform robustness exercises and report the results in Table A4. Along a wide range of possible values we consider, where $1/4 < \alpha < 1/2$, $0.75 < \eta < 0.95$, and $0.05 < r < 0.15$, the aggregate TFP loss only varies with a reasonable magnitude so that is not very different from our benchmark case.

Table 7 is very similar to Table 6 except that the values are reported for the unbalanced panel of Chinese firms. Financial frictions may reduce TFP through two channels – preventing entry and exit and misallocating capital among existing and ongoing firms. Not surprisingly, for any criterion based on age, size, ownership or political connection, the dispersion of output-to-capital ratio is more substantial across firms in the unbalanced panel than the balanced panel. The estimated TFP loss also increases to a range of 10.02%–15.15%, which highlights quantitatively the importance of the extensive margin of financial frictions on capital misallocation.

Taken together, the main result of this paper is that TFP losses due to financial frictions are about 5–15% in China during our sample period. This is remarkably close to findings in previous literature that uses quantitative model of financial frictions. In particular, Fig. 7 in Greenwood et al. (2013) shows the impact of a move to financial best practice on TFP for a large sample of countries. There, the countries with the worst financial system would improve TFP by about 20%.

5. Conclusion

This paper links the current literature on capital misallocation with a classic literature on investment-cash flow sensitivity. It provides a simple accounting device to compute the aggregate productivity loss due to capital misallocation in the presence of financial frictions. We make use of the differences in the stage of financial development of U.S. and China, and interesting institutional features within China, to apply various sample-splitting tests using an error-correction investment model. Our estimated investment-cash flow sensitivities imply an aggregate TFP loss around 5% for the balanced panel and 15% for the unbalanced panel of the Chinese manufacturing firms. Thus on the one hand, our finding echoes the literature on the

[8] One caveat that we should point out here is that the Sargan tests seem to reject the null of valid instruments in some of the sub-samples. This implies that although using an unbalanced panel substantially increases the number of observations, it also enhances the difficulty of finding valid instruments.

importance of financial frictions on efficiency loss by deterring entry and exit. On the other hand, our results are in line with Midrigan and Xu (2014) and Gilchrist et al. (2013), who find that financial frictions are unlikely to cause substantial efficiency loss among existing and ongoing firms.

This of course raises an interesting question, when we consider those large TFP losses identified in Hsieh and Klenow (2009), Brandt et al. (2013) and Song and Wu (2015) from capital misallocation in China. Banerjee and Dufflo (2005) offer a discussion on various causes of capital misallocation in addition to financial frictions. One possible candidate is studied in Wu (2018), who finds that the vast majority of capital misallocation in China is due to policy distortions instead of financial frictions. Another explanation, which is not specific to China thus more general, lies in the role of technology adoption. Midrigan and Xu (2014) conclude that the impact of financial frictions on technology adoption is more important than its impact on the allocation of capital across plants for explaining TFP. The role of financial frictions for technology adoption is the focus of the work of Cole et al. (2016).

Appendix A. Data

For U.S. Compustat, we first obtain the data from the earliest to the latest year as possible, for firms with SIC between 2000 and 3999 (inclusive), i.e. manufacturing firms. Since there is no data on birth year of a firm, we assume that its birth year is the first year that the firm entered our data set; hence, the firm is one year old for that year, two years old the following, and so on. We obtain the data on industry-level investment price deflator needed for construction of real investment and capital stock for the period of 1958–2009 from the NBER-CES (National Bureau of Economic Research) manufacturing industry database, and for this reason, we drop observations in our Compustat data set earlier than 1957 and later than 2007 before combining the two data sets together. Investment and cash flow are not readily constructed variables from Compustat; therefore, we construct investment as the difference between Items 30 (capital expenditures schedule V) and 107 (sales of property, plants, and equipments), and cash flow as the sum of Items 18 (income before extraordinary items) and 14 (depreciation and amortization). One of our main tasks is then the construction of real capital stock. Capital stock for firm i in industry m in year t are constructed by the perpetual inventory method. More specifically, we use the following formula

$$K_{it} = \begin{cases} (1-\delta) K_{i,t-1} + I_{it}, & \text{whenever } I_{it} \text{ is available} \\ (1-\delta) K_{i,t-1} + \left(BK_{it} - BK_{i,t-1}\right)/PI_{mt}, & \text{otherwise} \end{cases} \tag{14}$$

where I_{it} is the real investment of firm i in year t; BK_{it} is the book value of capital stock; PI_{mt} is the industry-level price index of investment in fixed assets in year t and industry m, taken from NBER. If a firm has data on the book value of capital stock in its first year, that value is used as the initial book value. Otherwise, we estimate the initial book value to be

$$BK_{i,t_0} = \frac{BK_{i,t_1}}{(1+g_i)^{t_1-t_0}} \tag{15}$$

where BK_{i,t_0} is the estimated initial book value of firm i who enters our data set in year t_0; BK_{i,t_1} is the earliest available book value of capital stock of firm i (t_1 denotes the corresponding year); and g_i is the average capital stock growth rate of firm i for the period we observe in the initial data set.

We construct real investment I_{it} as

$$I_{it} = \left(BK_{it} - BK_{i,t-1}\right)/PI_{mt} \tag{16}$$

when the initial data on book value of capital stock in year t and $t-1$ are available. The depreciation rate is assumed to be 10%, which is roughly the average difference between the constructed investment rate and sales growth rate for U.S. firms.

We then delete those observations whose value of sales, book value of capital, or real capital stock is negative or zero. We also delete firms which have experienced major merger or acquisition, as indicated by sales footnote. We use GDP deflator obtained from U.S. BEA (Bureau of Economic Analysis) website in the construction of real sales (Y_{it}), and real cash flow (CF_{it}). To further avoid firms experiencing major merger or acquisition, we replace the top and bottom 2.5% on year-by-year basis of investment rate ($I_{it}/K_{i,t-1}$), real sales growth rate (Δy_{it}), error-correction term ($k_{it} - y_{it}$), and cash flow rate ($CF_{it}/K_{i,t-1}$) by missing value so that our regression will ignore these observations, while we can preserve as many firms as possible when constructing the 10-year balanced panel.

Brandt et al. (2012) provide an excellent description on the Chinese Industrial Survey and implement a series of consistency checks between the firm-level data and the aggregated industry-level data reported in China Statistic Yearbooks. We, again, focus only on manufacturing firms. We construct a panel using unique firm IDs and clean the data by keeping firm-year with single-plant, with at least 8 employees, being actively in operation, and having positive sales and positive book value of capital stock. Construction of variables used in our estimation for this data set is similar to that mentioned in U.S. data, except that we now assume a 5% rate of depreciation, which is roughly the average difference between investment rate and sales growth rate for Chinese firms.

Table A1
Means (Standard Deviations) of Variables Used in Estimation.

	U.S.	China (Balanced)	China (Unbalanced)
I_t/K_{t-1}	0.185	0.107	0.211
	(0.269)	(0.251)	(0.523)
Δy_t	0.061	0.081	0.096
	(0.170)	(0.278)	(0.362)
$(k-y)_{t-2}$	1.245	−0.683	−1.025
	(0.698)	(1.029)	(1.304)
CF_t/K_{t-1}	0.323	0.196	0.297
	(0.571)	(0.259)	(0.455)

Table A2
AR(1) Models for I/K, Δy, CF/K, and $k-y$.

	U.S.	China (Balanced)	China (Unbalanced)
Investment Rate, I_t/K_{t-1}			
OLS	0.207**	0.152**	0.003
	(0.020)	(0.005)	(0.002)
Within	0.010	−0.078**	−0.229**
	(0.022)	(0.005)	(0.003)
GMM	0.179**	0.061**	0.039**
	(0.028)	(0.007)	(0.003)
Real Sales Growth, Δy			
OLS	0.170**	0.059**	−0.013**
	(0.017)	(0.004)	(0.001)
Within	0.003	−0.108**	−0.249**
	(0.016)	(0.004)	(0.002)
GMM	0.169**	0.023**	−0.016**
	(0.024)	(0.005)	(0.002)
Cash Flow Rate, CF_t/K_{t-1}			
OLS	0.556**	0.642**	0.379**
	(0.021)	(0.006)	(0.003)
Within	0.275**	0.239**	−0.030**
	(0.022)	(0.007)	(0.004)
GMM	0.396**	0.254**	0.216**
	(0.038)	(0.014)	(0.006)
Error Correction Term, $k-y$			
OLS	0.890**	0.895**	0.772**
	(0.006)	(0.002)	(0.001)
Within	0.564**	0.521**	0.253**
	(0.016)	(0.005)	(0.002)
GMM	0.692**	0.607**	0.463**
	(0.041)	(0.010)	(0.004)

Note:
1. Robust standard errors are reported in parentheses.
2. *Significant at the 5% level; **Significant at the 1% level.

Table A3
Forecasting Models for Sales Growth–Dependent Variable Δy_t; OLS.

	China	U.S.
I_{t-1}/K_{t-2}	0.079**	0.077**
	(0.006)	(0.017)
I_{t-2}/K_{t-3}	0.057**	−0.036*
	(0.005)	(0.014)
Δy_{t-1}	0.003	0.013
	(0.006)	(0.026)
Δy_{t-2}	−0.003	−0.111**
	(0.005)	(0.023)
CF_{t-1}/K_{t-2}	0.040**	−0.006
	(0.008)	(0.012)
CF_{t-2}/K_{t-3}	−0.029**	−0.011
	(0.008)	(0.012)
Test statistics for H_0		
chi (1)	3.35	3.90
Prob > chi2	0.067	0.048

Note:
1. Robust standard errors are reported in parentheses.
2. *Significant at the 5% level; **Significant at the 1% level.
3. H_0: coefficient of CF_{t-1}/K_{t-2} + coefficient of $CF_{t-2}/K_{t-3} = 0$.

Table A4
TFP Loss under Alternative Parameter Values for the Balanced Panel.

	$\boldsymbol{\alpha = 1/3}$ $\boldsymbol{\eta = 0.85}$ $\boldsymbol{r = 0.10}$	$\boldsymbol{\alpha = 1/4}$ $\eta = 0.85$ $r = 0.10$	$\boldsymbol{\alpha = 1/2}$ $\eta = 0.85$ $r = 0.10$	$\alpha = 1/3$ $\boldsymbol{\eta = 0.75}$ $r = 0.10$	$\alpha = 1/3$ $\boldsymbol{\eta = 0.95}$ $r = 0.10$	$\alpha = 1/3$ $\eta = 0.85$ $\boldsymbol{r = 0.05}$	$\alpha = 1/3$ $\eta = 0.85$ $\boldsymbol{r = 0.15}$
Young	3.99%	2.64%	7.00%	2.63%	6.80%	4.13%	3.85%
Old							
Small	5.24%	3.47%	9.22%	3.46%	8.96%	5.43%	5.07%
Large							
Non-SOEs	4.97%	3.29%	8.71%	3.28%	8.42%	5.15%	4.80%
SOEs							
Non-Union	5.06%	3.35%	8.91%	3.34%	8.69%	5.25%	4.89%
Union							

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