HOW COSTLY IS FINANCIAL CONSTRAINT?

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HOW COSTLY IS FINANCIAL CONSTRAINT?

by

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Abstract

Financial constraint is a status of a firm when the firm's actual capital stock is lower than its desired capital stock – the capital stock level the firm would have chosen in the absence of financial frictions. Financial constraint occurs when the cost of raising external funds is higher than the cost of internal funds (cost constraint) or when there are limits on how much firms can raise external funds (quantity constraint). Under a perfect capital market, real investment decision is independent of financial status. In an imperfect capital market, various financial frictions break down this independence and finance becomes an important determinant of firm investment and productivity. As a result, we expect financial frictions to play significant roles in governing the performance of individual firms and of the economy as a whole.

Using firm-level datasets and employing newly-developed microeconometric techniques, this thesis investigates three interesting implications of financial constraint on investment and productivity. First, how to determine whether a firm is financially constrained and the effect of financial constraint on firm-level investment; second, how to quantify the impact of financial frictions on the aggregate productivity loss of the economy as a whole through capital misallocation; and third, how to detect whether financial constraint affects the productivity of individual firms endogenously.

Chapter 1 provides motivation of this thesis, together with general reviews of related literatures on financial constraint.

Chapter 2 investigates empirically the most controversial, yet influential, measure of financial constraint –investment-cash flow sensitivity– using firm-level datasets of U.S. and China. Under a perfect capital market, investment decision is independent of a firm's financial status. Therefore investment will not exhibit any sensitivity to cash flow when investment opportunities are properly controlled for. Imperfections in the capital market, however, can cause a wedge between the cost of internal and external finance. Therefore investment will respond positively to the availability of cash flow if a firm is financially constrained. As a benchmark, this model is applied to a panel of U.S. manufacturing firms, which we expect to be not/little constrained, and a panel of Chinese manufacturing, which we expect to be constrained. We also apply the model on different groups of Chinese firms. Our results consistently support: 1. the hypothesis that at least some of the Chinese firms are financially constrained; 2. the evidence from the data that there is a capital misallocation in China; and 3. the idea that more productive firms are generally more constrained.

Chapter 3 examines capital misallocation within China. Capital misallocation exists when

firms have different marginal revenue product of capital (MRPK). This dispersion of MRPK across firms can be due to financial friction or policy distortion. Financial friction in capital misallocation means that although a firm has a high MRPK compared to another firm, this firm cannot increase its capital investment to take advantage of its high MRPK at all, since it needs to raise the necessary fund externally, and since its financial status is viewed by potential investors or lenders as not desirable. On the other hand, even though two firms have identical financial status, they might still receive different treatment with regard to the rate of return or interest rate required by investors or lenders. We call this kind of distortion "policy distortion". The main contribution of this chapter is to disentangle the effect of policy distortion and financial friction in explaining the difference in MRPK across different groups of firms, using a propensity score matching. We find that financial frictions cause an 8.6% total factor productivity loss, which accounts about 30% of the overall loss.

While Chapter 2 and 3 take the firm-level productivity as exogenous, Chapter 4 studies whether financial constraint may affect a firm's productivity endogenously. Though there are many studies on the effect of finance on firm's investment, how financial constraint affects firm's productivity, which is a prominent factor for a firm's performance and a country's economic growth, has not received much attention. In addition, those few studies on this linkage have often not been able to produce reliable results due to econometric issues involved. More specifically, the so-called two-stage approach first estimates firm's productivity using production-function-estimation approaches such as Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2006), with exogenous productivity process, then uses this newly generated productivity to regress on various financial variables to identify financial effects on productivity. However, if finance does affect productivity, not-including financial variables as regressors in the productivity process would lead to biased and inconsistent estimates of production function parameters as well as inconsistent estimation of productivity. We attempt to resolve this issue by augmenting various measures of financial constraint directly into the proxy function and the second-stage productivity regression under the Ackerberg, Caves, and Frazer (2006) approach.

Chapter 5 summarizes our results and contributions. We also discuss various potential future researches related to the thesis.

Chapter 1

Introduction

1.1 Motivation

According to Modigliani and Miller (1958), in a world of perfect capital markets, finance is irrelevant for real decisions. So, finance or financial sector does not play any role in the economy at all, since economic condition is affected only by real variables such as real output, real investment, and so on. Why do we need to study finance then? Well, of course, nothing is perfect. The world is not perfect, as are its capital markets; financial friction (or financial constraint) exists. Finance can be an important factor in determining economic growth in that case. In fact, the idea that finance promotes economic growth was recognized as early as Schumpeter (1912). However, this view had not fared well with numerous researchers, particularly Lucas (1988). Maybe the first acceptable empirical evidence that suggests financial development enhances productivity, thereby, economic growth is King and Levine (1993). Many researchers from then on have tried to investigate this finance-growth relationship more rigorously both at macro-level and micro-level. This thesis attempts to fit in these literatures by investigating various issues regarding past researches, applying more reliable techniques on existing problems, and providing new insight on the role financial sectors play, focusing particularly on the problem of firm's financial constraint using firm-level dataset.

Studies of the effect of financial friction on the economy are very important. It is now widely accepted that total factor productivity (TFP) accounts for most of the differences in GDP per capita across countries. But what cause TFP in different coutries to be different? Because less-developed countries generally have poorer financial system compared to more-developed countries, maybe it is the relative inefficiency of the financial market in allocating funds to the right firms that hamper the productivity of the country. In general, as pointed out in Midrigan and Xu (2014), this inefficiency (or friction) in the financial market can reduce productivity via two channels. First, potentially good firms, but with no or little capital, cannot enter the market. Second, existing firms that have good investment opportunities might have to forego those opportunities, again due to no or little internal capital and its inability to raise external funds due to financial friction. In addition to not allocating funds to good firms, frictional capital market might even actually allocate funds to bad firms, resulting in further loss of productivity and economic growth. One of our main goals in this thesis is to quantify the impact of financial friction (and policy distortion) on TFP, using an extensive firm-level manufacturing data set for China, an emerging economy with high GDP growth rate despite its relatively less-developed financial system. Firm-level data set for U.S., an economy with developed financial system and low friction, is sometimes employed for comparison purposes.

Understanding the role of finance in the economy is very essential for policy makers. Without this understanding, policy that is designed to increase economic performance might be ineffective or even backfire. Other (financial) policies that can raise firm's, and ultimately country's, growth will be overlooked. With convincing evidence that finance matters, it opens up more plausible and effective financial policies that can help ameliorate economic conditions to be implemented. Researches on various aspect of financial sectors such as the impact of political distortion, legal requirements, and regulatory determinants on financial market, when deemed reliable, can be indispensable assets for policy-making decisions.

We have mentioned earlier the term financial constraint, in addition to the widely known term financial friction. What exactly do we mean by financial constraint? What causes financial constraint? And why do different firms have different level of financial constraint? The answers to these questions can be easily answered in our following section.

1.2 Financial Constraint

Financial constraint occurs when the cost of raising external funds (equity or debt) is higher than the cost of internal funds (cost constraint) or when there are limits on how much firms can raise external funds (quantity constraint). In order to better understand why financial constraint exists, we will provide and discuss the most prominent causes of financial constraint, that also were given in Fazzari et al (1988). They are transaction costs, tax advantages, agency problems, costs of financial distress, and asymmetric information. We will divide our discussion into two parts –new share issues (equity finance), and debt finance– and discuss the corresponding causes in detail.

New Share Issues: The issues of new share are typically carried out by underwriters (banks or other types financial institutions). There are usually three roles played by underwriters: first they provide financial advice to firms and help them with issuance procedure, then they purchase the new shares issued, and lastly they resell it to the public. The difference between the selling and the buying price is called 'underwriting discounts'. We can obviously see why this underwriting discount is the cost to the issuing firm. Other costs include registration fees and taxes, and selling and administrative expenses. Together, the "transaction" costs (per share) of issuing new share may vary differently; usually, they are higher for small and/or seasoned offerings compared with large and/or initial public offerings.

Historically, in U.S. and many other countries, internal finance provides tax advantages over new share issues due to lower capital gains tax than dividend income tax. Firms, therefore, can avoid some taxes for their owners by just retaining all their earnings rather than paying out dividend and issuing new shares later on (to finance this dividend payout) because investors can simply sell their shares in the market whenever they want to get back some cash; hence, they are subject to a smaller tax on their capital gains (King, 1974; Auerbach, 1979). Today, the tax rate on capital gains and dividends are roughly the same. Nevertheless, capital gains still have another advantage over dividends. Tax-payers have to pay dividends tax immediately, but they can defer capital gains tax until they actually sell the shares and realize the capital gains. In this sense, stockholders can decide when to sell their shares, and hence, when to pay the tax on capital gains. The longer they wait, the less the present value of the capital gains tax liability, (Brealey, Myers and Allen, 2010, p. 407).

New share issue is also subject to the asymmetric information problem, which is the most significant cause of making external finance more costly than internal finance. Similar to the 'lemon' problem first introduced by Akerlof (1970), the sellers of new shares (managers) have more information about their firms compared with the potential buyers (investors). Since there are both bad and good firms in the market, the less-informed investors will value a good firm as an average firm; hence, provide a less-than-fair price to the firm's share. This 'premium' paid by the relatively good firms in turn generates the cost wedge of internal and external finance. Myers and Majluf (1984) incorporates this idea and explains it analytically using the Q model of investment. In their model, firms will issue new shares to support their investment only if the existing shareholders' wealth increases after that, at least ex ante. Let Y denote the 'intrinsic value' of the firm; it is also the existing shareholders' wealth if the firm does not issue new shares to invest. Let I be the cost of new investment, and let Y' be the gross returns from this investment. Since the market cannot distinguish between good and bad firms, they will value this firm at an average value, say V. Knowing this, firms will invest only if the existing shareholders' wealth in the case of not issuing, Y, is less than or equal to their wealth when firms issue new shares and invest, $(Y + Y')\, V/\,(V + I)$, or equivalently, only if

$$Y'/I \geq Y/V \tag{1.1}$$

The left hand side of equation (1.1) is simply the firm's marginal Q. In the absence of asymmetric-information problem, the market value of the firm assigned by investors will be correct, i.e. $V = Y$; hence, the optimal rule for firm to issue new shares and make the investment is the conventional marginal $Q \geq 1$. However, with asymmetric information, the market value V assigned by investors will be smaller than the intrinsic firm's value Y for good firms, and firms will make the investment by issuing new shares only when the marginal Q is large enough (at least Y/V, which is larger than 1). The amount $Y/V - 1$ can be seen as the cost premium of equity finance.

Debt Finance: 'Trade-off' theory of capital structure is the standard argument of why the cost of debt is different (higher in general) than internal finance. Although debt gives firm some tax advantages due to its tax-deductible feature, cost of financial distress will generally be more significant, especially when its debt ratio is high. Financial distress occurs when firms cannot honor or have difficulties paying off their financial obligation to creditors, which can lead to bankruptcy in some cases.

When a firm is in trouble, although it seems like both lenders and stockholders want it to recover, their individual objective might conflict one another (agency problem). The agency problem arises due to the limited-liability feature, usually found in corporations, of debt contracts, i.e. owners of the firm do not need to pay their own cash for the debts the firm borrowed in case of bankruptcy. This creates incentives for firm managers, who are assumed to act in the interest of stockholders, to sometimes undertake actions counter to the interests of creditors, for instance, the managers might forgo some positive net-present-valued (NPV) investment and even accept those negative NPV ones. Firm also has incentives to issue new debt, thereby, lowering the value of its existing debt. Lenders know this, so they might require firms to agree to some debt contracts that can protect them from being exploited. However, the costs of writing, overseeing, and enforcing the debt contract can be large, and are usually born by the firm itself. It can be even more costly if the restrictions found in the contracts limit firms from making good management, for instance, by not allowing firms to raise more debts (to finance good investment opportunities) even when internal finance is low. Consequently, this agency problem can generate huge costs of external debt finance over internal finance.[1]

The problem of asymmetric information in debt markets arises due to similar reasons for new share issues. Lenders cannot distinguish between good and bad borrowers (firms); therefore, they charge an average interest rate to all firms, making good firms face higher cost of new debt than they deserve; financial constraints occur naturally. In some cases, firms might not be able to borrow at all even though they are observationally indistinguishable to the lenders, no matter how much interest rate they are willing to pay. This 'credit rationing' equilibrium is first investigated in Stiglitz and Weiss (1981). Either adverse selection or moral hazard problem can be used to explain this kind of rationing. Adverse selection in the market for debts means that usually only high-risk (bad) firms will want to borrow at high interest rates. Consequently, raising interest rates might lead to most or all high-risk borrowers, who are not able to pay back the loan, making the banks lose their money. On the other hand, as the interest rate and other terms of the contract change, the behavior of the borrower is likely to change (moral

[1] For details, see Myers (1977), and Jensen and Meckling (1976).

hazard). Stiglitz and Weiss (1981) shows that higher interest rates, by decreasing the return on projects which succeed, encourage firms to engage in projects with small chance of success, but which result in high payoffs if successful, i.e. riskier investment projects, increasing the chance of firms not being able to pay back. In the end, banks might decide not to increase interest rates at all even though there is excess demand for loan at current interest rate, thereby, some firms are 'credit rationed'.

Chapter 2

Testing for Financial Constraints on Chinese Manufacturing Firms

2.1 Introduction

There are two main reasons for studying investment, (Romer, 2006, p. 386). First, an economy's output is determined by the combination of firms' investment demand and national supply of saving; therefore, investment is a very important factor in determining the standards of living of that economy. Second, fluctuation of the economy in the short-run can also be explained, and is usually caused, by fluctuation in investment. In Modigliani and Miller (1958) world, investment decision is independent of financing decision; in reality, financial frictions break down this independence and become an important determinant of firm investment. Financial friction caues the cost of raising external funds (equity or debt) to be higher than the cost of internal funds (retained earnings). Without such frictions, Modigliani and Miller (1958) showed that firm's capital structure is not relevant with real investment decisions making; external finance works just as perfectly as internal finance. There is, however, a large number of theoretical and empirical researches in support of the existence of this friction. When external finance and internal finance are not perfect substitutes, firms might base their investment decision not only on their demand to invest, but also on the availability of internal finance, ability to issue new debt or equity, and the functioning of their respective capital markets. This interdependency arises because firms prefer internal over external finance due to its relatively low opportunity cost. Consequently, a term 'constrained firms' is introduced to refer to firms whose investment demand exceeds internal finance and who face the above-mentioned higher cost of external to internal finance.

Different firms with different degrees of financial constraints are expected to exhibit different patterns in their investment and financial behavior. Fazzari et al (1988) investigates the role of cash flow in explaining investment behaviour by firms, thereby introducing the use of 'investment-cash flow sensitivity' as a measure of firm's degree of financial constraints. Investment-cash flow sensitivity is defined as the sensitivity of a firm's investment with respect to their cash flow, i.e. it shows how much a firm would invest out of a one-dollar increase in its cash flow. Based on some a priori measure–magnitude of dividend payouts– Fazzari et al (1988) is able to classify constrained and unconstrained firms, and their results showed that more-constrained firms exhibit higher investment-cash flow sensitivity than less-constrained firms, as more-constrained firms rely more heavily on internal finance in financing their investment due to higher internal-external cost wedge whereas less-constrained/non-constrained firms can more easily use external finance to fulfill their investment need; hence, respond less actively to their cash flow change. This finding is opposed by Kaplan and Zingales (1997) who provided both theoretical and empirical contradictions. On theoretical ground, 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, which are easily violated. On empirical basis, instead of relying only on quantitative data to make their classification of firms' degree of financing constraint, they also investigate firms' qualitative data such as management's discussion of liquidity and annual report. Strikingly, with this classification, they found that firms classified as less-financially-constrained exhibit significantly greater investment-cash flow sensitivities than those firms classified as more-financially-constrained. This chapter, however, applies an error-correction specification of investment which can be found in Bond et al (2003). According to Bond et al (2003), since the model used in Kaplan and Zingales (1997) does not account for capital adjustment cost, which is incorporated in the model we are using, their result does not contradict with ours. Moreover, in Kaplan and Zingales (1997), even though it is found that more-financially-constrained firms do not necessarily exhibit higher sensitivity, it remains the case that unconstrained firms would display no excess investment-cash flow sensitivity. In this regards, finding that one type of firm with positively significant cash flow coefficient in the regression will undoubtedly indicate the firms are constrained, while unconstrained firms should produce insignificant cash flow coefficient.

The higher sensitivity of investment to cash flow has been largely found; for instance, for within-country comparison, in younger and smaller firms compared with older and larger firms (see, for example, Hovakimian and Hovakimian (2009)), and for cross-country comparison, in less financially-developed economies compared with more financially-developed ones (see, for example, Love (2003)). These results support the findings by Fazzari et al (1988) due to the fact that younger and smaller firms, and firms in less financially-developed economies are more likely to be more financially constrained. Indeed, younger and smaller firms should, in general, be riskier and face more asymmetric information problem than older and larger firms; hence, lenders/investors are less willing to lend and invest, and would only do so at a high rate of interest, making young and small firms financially constrained. This asymmetric information problem is also more severe in less financially-developed economies, making firms in these economies more financially constrained than their counterparts. As a result, the findings of higher investment-cash flow sensitivity in younger and smaller firms, and firms in less financially-developed economies consistently support the above idea that financial constraint problem should be more severe in these groups of firms.

The aim of this chapter is to: 1. study financing constraint conditions for Chinese firms as a whole; 2. investigate which types of firms are likely to be more constrained and why; 3. use financial constraint to support evidence of capital misallocation in China. Our chapter is motivated by the evidence, presented in the data, of capital misallocation in China. Capital misallocation exists due to differences in $MRPK$ (marginal revenue product of capital) across different group of firms: younger, smaller, DPEs and less politically-connected firms have higher levels of capital productivity compared with their counterparts. Capital misallocation implies that these firms cannot take advantage of their high capital productivity by investing more, due to perhaps financial constraint reason. We want to explore whether this is actually the case, by using investment-cash flow sensitivity as a measure of financial constraint.

We achieve these by investigating firm's investment-cash flow sensitivities in an error correction specification of investment, which can be found in Bond et al (2003). Error-correction investment specification is found by nesting a firm's long-run demand-for-capital specification in a flexible short-run investment dynamics. This error-correction specification has the advantage over the usual Q-model of investment for it avoids the use of Tobin Q, which is usually mismeasured practically. We will estimate our model using the first-differenced GMM method for panel data developed by Arellano and Bond (1991), which is shown to produce consistent estimates when the number of cross-sectional observations tends to infinity (large enough) with fixed time period, as is usually the case for panel data. Some OLS and within-groups estimates will be reported for comparison. As a benchmark, our model is applied to a panel of U.S. manufacturing firms from Compustat database. We would expect firms in U.S. to be less constrained (unconstrained) than their counterparts in China, simply because the financial market in U.S. is better established and more developed. Different sample-splitting tests–based on age, size, ownership type, and political connection– within China will be performed to enable us to explore more different types of Chinese firms that might face differential constraints. The corresponding sample-splitting tests based on age and size will also be performed for US for comparison. We would expect more-constrained firms, in any types of tests, to exhibit higher investment-cash flow sensitivity (larger coefficient on cash flow variable), if the coefficients are estimated correctly. Empirically, however, it is important that we are careful in interpreting the results when we find the coefficient of one type of firms is higher than another. It is well-known that this kind of regression is subject to omitted expected future profitability variables. For example, if high cash flow today indicates a better tomorrow (higher expected future profitability), a firm might invest more (hence, high sensitivity) even though it is not constrained at all. For this reason, we will investigate and discuss more on the relative predictability of cash flow on future profitability. We examine the reasons why different group of firms face different degree of financial constraint by exploring their risk and labor union characteristics, and suggest two main underlying factors affecting the degree of financial constraint: financial characteristics and policy distortion. Finally, we show that our calculated investment-cash flow sensitivities consistently support the evidence that there is a capital misallocation in China, and the idea that more productive firms are generally more constrained.

Although evidence that financial constraint is an impediment to investment and growth is vast, most empirical researches about financial constraints focus on developed countries; relatively few researches have examined this issue within the context of a developing, and transition, economy, like that of China. Li et al (2008), who examined the impact of political connections, using Chinese Communist Party membership as proxy, on firms' financial constraints and performance, found that Party membership facilitates private entrepreneurs in obtaining loans from banks or other state institutions. A similar positive impact of political connections on financial constraints is found by Cull et al (2013), who uses government intervention in Chief Executive Officers appointment as a proxy for firms' political connections. We analyze similar issue, using information on whether a firm has a labor union as an alternative proxy. With a more extensive data set and new proxy for political connection, our results provide further evidence that political connections ease firms' financial constraints.[1] Poncet et al (2010), who used investment-cash flow sensitivities to investigate the degree of financial constraint of private firms (DPEs), foreign-owned firms (FIEs), and state-owned firms, which is defined as the pooled state-owned (SOEs) and collectively owned enterprises (COEs), found that private Chinese firms are credit constrained while state-owned firms and foreign-owned firms in China are not. The regression model used in their study is an empirical Euler specification, which relies heavily on the assumption of symmetric and quadratic adjustment cost functions. We apply a more reliable dynamic GMM method on a less restrictive error correction model and, together with the separation of COEs from SOEs and HMTs (Hong Kong, Macau, and Taiwan firms) from FIEs, find that the results for (the unconstrained) SOEs, COEs, and FIEs and (the much-constrained) DPEs are consistent with the finding of Poncet et al (2010).[2] Additionally, we also find that HMTs has a pretty high degree of financial constraint, though observably lower than that of DPEs.[3] Apart from testing which Chinese firms are constrained or not, we also investigate why different types of firms have different degree of financial constraints. We conject the differences in degree of financial constraints by different groups of firms to different risk

[1] See Khwaja and Mian (2005) and Faccio (2006) for more discussions of the impact of political connection on firm's financing and performance.

[2] A quite contrasting result can be seen in Chow and Fung (1998). COEs are found to be less liquidity-constrained than SOEs in terms of the availability of cash flow, i.e. lower investment-cash flow sensitivity. Their results, however, are derived from the use of only a short panel (1989-1992), and more importantly, a static panel model with no firm-fixed effect.

[3] Other papers supporting the higher degree of financial constraint faced by Chinese private firms include Brandt and Li (2003), Guariglia et al (2011), and Héricourt and Poncet (2009).

characteristics and degree of political connections (proxied by labor union). The data, indeed, supports our conjecture. Those more financially-constrained types of firms are the ones with high risk and lower level of political connections on average. Finally, we use our investment-cash flow sensitivities result to support the evidence of capital misallocation. By using the difference between sales and capital stock as a proxy for firm's capital productivity, we find that younger, smaller, DPEs and less politically-connected firms have higher levels of capital productivity on average, compared with their counterparts, and therefore, there is a clear indication of capital misallocation. Capital misallocation implies that these firms cannot take advantage of their high capital productivity by investing more, due to perhaps financial constraint reason. Indeed, our investment-cash flow sensitivity results show that younger, smaller, DPEs, and less politically-connected firms are the most contrained types of firms.

The rest of this chapter is organized as follows. Section 2 provides related literature reviews of the use of investment-cash flow sensitivity as a measure of financial constraint. Section 3 briefly describes the empirical model and data sets used. Section 4 provides and discusses our empirical results. Section 5 concludes.

2.2 Investment-Cash Flow Sensitivity

Investment-cash flow sensitivity is defined as the degree to which firm invests out of their cash flow. Higher investment-cash flow sensitivity indicates that firm spends more of their retained earnings/net cash flow for investment. As indicated in Fazzari et al (1988), if there is only a small cost disadvantage of external finance over internal finance (little financial constraint), changes in internal finance should not really affect investment: firms can just use external finance to fund investment when internal finance fluctuates. However, if there is a huge cost disadvantage (much financial constraint), firm's investment should be driven by fluctuations in cash flow. Therefore, more-financially-constrained firms should have greater investment-cash flow sensitivities compared to less-constrained firms.

Several investment models were adopted in this investment-cash flow study, but perhaps the most widely adopted is the Q-model of investment, as given by:

$$\frac{I_{it}}{K_{it}} = \theta_1 \frac{CF_{it}}{K_{it}} + \theta_2 Q_{it} + d_t + \eta_i + v_{it} \tag{2.1}$$

where Q is a measure of average Tobin's Q; CF is cash flow; v is an error term; i is the firm index; t is the time index; d_t is a time dummy and η_i is an unobserved firm-specific effect. This Q-model of investment is based on the idea that capital investment becomes more attractive as the value of capital increases relative to the cost of acquiring the capital (higher Q). More formally, as can be found from Hayashi (1982), this Q model is derived from the first-order condition for the optimal capital stock under four assumptions: 1. firms are price takers in all markets; 2. capital markets are perfect; 3. the revenue function is homogenous of degree one in capital stock and investment, (K_t, I_t); and 4. firm faces a symmetric and quadratic adjustment cost around the rate of depreciation. Moreover, given all these assumptions, the theory suggests that measures of financial variables are not relevant for explaining firm's optimal investment, conditional on average Q. Consequently, firms which face no financial constraint should have insignificant investment-cash flow sensitivity, θ_1. However, if frictions exist in the financial market, financial variable will be an important factor in determining firm's investment, so θ_1 should be positive and significant for such constrained firms. Furthermore, the coefficient on CF_{it}/K_{it}, i.e. θ_1, should be higher for more-financially-constrained than for less-financially-constrained firms, as is evident in Fazzari et al (1988). The use of this model requires some cautions. One of them is the mismeasurement errors of Q. In principle, Tobin's Q of a firm can be computed accurately. The market value of the firm's asset can be measured using the market value of the firm's debt and equity whereas the replacement value/cost can be derived from the price at which the asset can be purchased or sold using the firm's accounting standard. In practice, however, several difficulties arise that can hinder our calculation of the true Q. One of them involves the calculation of market value and replacement cost of intangible assets. Some kinds of estimation/algorithm need to be employed to come up with some estimate of this Q; hence, it might be subject to mismeasurement errors. The use of Q in time-series regression in explaining investment behavior, therefore, might result in biased and inconsistent estimators. In an attempt to avoid using this mismeasured Q as an independent variable in explaining investment demand, our chapter, instead, adopts the empirical error-correction specification developed by Bond et al (2003). More details about this specification will be given in our model design in the next section.

The use of investment-cash flow sensitivity as a measure of financial constraint has been a subject of lots of controversy. The most commonly used argument against it is the Kaplan and Zingales (1997)'s critique. In Kaplan and Zingales (1997), it is shown theoretically that there is no monotonic relationship between the degree of financial constraint and investment-cash flow sensitivity. The relationship actually depends on both the production and cost functions. Moreover, using the same data set as Fazzari et al (1988), they find that more-constrained types of firms actually exhibit lower investment-cash flow sensitivity. There are, however, two important points to highlight. First, in Kaplan and Zingales (1997), both theoretically and empirically, it is found that unconstrained type of firms still exhibits no investment-cash flow sensitivity. So, our results of insignificant cash flow effect in any (sub)sample undoubtedly indicate that firms in that (sub)sample are unconstrained. Second, their model does not include adjustment cost of capital, and thus, cannot be considered as complete. Our empirical specification used is of the error-correction investment model employed in Bond et al (2003). This specification is derived from a model of firm's capital demand, allowing for adjustment cost and short-run investment dynamics. Kaplan and Zingales (1997)'s critique, therefore, does not apply in our case. Our results that more-constrained firms have higher investment-cash flow sensitivity are not inconsistent with them. Furthermore, using a dynamic investment problem with strictly convex costs of adjustment, Bond and Soderbom (2013) shows that there is a monotonic relationship between the cost premium for external funds and the sensitivity of investment to cash flow, conditional on marginal q.

2.3 Empirical Implementation

2.3.1 Model

We employ the following error-correction specification of investment, which can be found in Bond et al (2003), as our empirical model:

$$\begin{aligned} \frac{I_{it}}{K_{i,t-1}} &= \rho\frac{I_{i,t-1}}{K_{i,t-2}} + \gamma_0\Delta y_{it} + \gamma_1\Delta y_{i,t-1} + \phi\left(k_{i,t-2} - y_{i,t-2}\right) + \pi_0\frac{CF_{it}}{K_{i,t-1}} + \pi_1\frac{CF_{i,t-1}}{K_{i,t-2}} \\ &\quad + d_t + \eta_i + v_{it} \end{aligned} \tag{2.2}$$

To derive this specification, it is assumed that firm's optimal level of capital is a linear function of output and user cost of capital (in log form), i.e.

$$k_{it} = a_i + y_{it} - \sigma j_{it} \tag{2.3}$$

where k is the natural logarithm of the optimal capital stock, y is the log of output, j_{it} is the log of the real user cost of capital and a_i is the firm-specific intercept. This assumption 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 ($\sigma = 0$). It is also consistent with a Cobb-Douglas production function, with or without constant returns to scale, when $\sigma = 1$. 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 user cost of capital can be controlled for by including both time-specific and firm-specific effects– the model of capital stock above can acount for the presence of adjustment costs by nesting equation (2.3) within a dynamic regression model. Following Bond et al (2003), we choose an autoregressive-distributed lag specification ADL(2,2), as follows:

$$k_{it} = \alpha_1 k_{i,t-1} + \alpha_2 k_{i,t-2} + \beta_0 y_{it} + \beta_1 y_{i,t-1} + \beta_2 y_{i,t-2} + d_t + \eta_i + v_{it} \tag{2.4}$$

Long-run unit elasticity of capital with respect to output, as can be found in equation (2.3), implies that $(\beta_0 + \beta_1 + \beta_2)/(1 - \alpha_1 - \alpha_2) = 1$. Solving for β_2, and substituting into equation (2.4) gives

$$\begin{aligned} \Delta k_{it} &= (\alpha_1 - 1)\,\Delta k_{i,t-1} + \beta_0 \Delta y_{it} + (\beta_0 + \beta_1)\,\Delta y_{i,t-1} - (1 - \alpha_1 - \alpha_2)\,(k_{i,t-2} - y_{i,t-2}) \\ &\quad + d_t + \eta_i + v_{it} \end{aligned} \tag{2.5}$$

We will investigate the validity of this long-run restriction in our empirical analysis. 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 firm would decrease their investment when actual capital stock is above the optimal level, and vice versa.. From equation (2.5), we can derive our main regression model

(2.2) 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 and lagged cash flow terms as additional regressors.

This model has an advantage over the Q model as it avoids using the possibly mismeasured Q in the estimation. However, as mentioned before, one needs to be careful with the interpretation of these cash flow coefficients. Even though a significant cash flow coefficient could indicate the presence of financial constraints, the coefficient can still be significant even in the absence of financial constraint. The former will be the case if cash flow conveys no information about future profitability. If, however, cash flow can help predict future profitability or sales, for instance, investment will be affected significantly by the change in cash flow even in the case of no financial constraint at all. This is because investment demand depends on future desired capital stock, for example, if firm faces strictly convex adjustment costs, and because future desired capital stock in turn depends on expected future output or sales. Therefore, to make the comparison between US and China reliable, our chapter will investigate directly whether or not current or lagged cash flow variables forecast future sales growth or cash flow (profitability indicators) differently across both countries. Similar investigation has been done for other sample-splitting tests, though, not reported in the chapter.

Our regression models are estimated using '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 endogenous explantory variables, as can be found in equation (2.2). Appendix A reviews this dynamic panel data method in detail.

2.3.2 Data

The data sets used in our study are annual firm-level 10-year balanced panels from Standard and Poor's Compustat for U.S. and from Chinese Industry Survey (which the National Bureau of Statistics of China has conducted yearly since 1998) for China, covering the 1998-2007 period.

For U.S., 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

$$K_{it} = \begin{cases} (1-\delta) K_{i,t-1} + I_{it} \text{ , whenever } I_{it} \text{ is available} \\ (1-\delta) K_{i,t-1} + (BK_{it} - BK_{i,t-1}) / PI_{mt} \text{ , otherwise} \end{cases} \tag{2.6}$$

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

$$BK_{i,t_0} = \frac{BK_{i,t_1}}{(1+g_i)^{t_1-t_0}} \tag{2.7}$$

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

$$I_{it} = (BK_{it} - BK_{i,t-1}) / PI_{mt} \tag{2.8}$$

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), and real cash flow (CF). 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 ($k-y$), 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. The final 10-year balanced panel for the period 1998-2007 for U.S. we obtain consists of 900 firms.

For Chinese data set, the data description provided by Brandt et al (2012) helps motivate and facilitate our panel construction and data cleaning a lot. We, again, focus only on manufacturing firms, defined in the Chinese data set by the 4-digit industrial code between 1300 (inclusive) and 4400. In contrast to Brandt et al (2012) who matches firm across different years using firm IDs, names, names of legal person representatives, phone number plus city code, and founding year plus geographic code plus industry code plus name of town plus name of main product, only firm IDs match is performed in our chapter (as we have some difficulties dealing with Chinese characters). As indicated in Brandt et al (2012) that about 96% of all their year-on-year matches are based on firm IDs, our resulting matched data set is still very highly comparable with theirs, and hopefully, of the true matched population. After this matching, we end up with an unbalanced panel of firms, with 130,103 firms in 1998 and 303,949 firms in 2007. Then, we clean the data by keeping firm-year with at least 8 employees (as those with less than 8 employees fall under a different legal regime, i.e. they are not legally considered as firms), 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 use 5% rate of depreciation (which is roughly the average difference between investment rate and sales growth rate for Chinese firms). The final 10-year balanced panel we obtain consists of 13,329 firms. Table 2.1 reports the mean values and standard deviations of the variables used in our regression model for both balanced panels. To the extent that firm that makes net disinvestment in any year means they have more than enough cash than they require for investment, that firm is, with little doubt, unconstrained. Only those firms with positive or zero net investment can be financially constrained; hence, are of our interest. For this reason, before running the regression, we replace those firm-year with negative investment rate by missing value so that our regression will ignore these observations while allowing the same firm to be included in the regressions in some other years when that firm make non-negative investment.

2.4 Result

We start off by considering the time series properties of the variables used in equation (2.2). 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 2.2 reports the estimation results of simple AR(1) models of $I_t/K_{t-1}, \Delta y, CF_t/K_{t-1}$, 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 2.2 also reports within-groups and GMM estimators for comparison purposes.[4] 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.

Table 2.3 reports our GMM results for the full sample of US and China. The instruments used were 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 IVs. As can be seen, the coefficient on cash flow is highly positively significant for China, while insignificant for U.S., indicating that Chinese

[4]The instruments used to calculate these GMM estimators are lagged of the series dated $t-2$ and $t-3$.

firms are pretty much financially constrained and U.S. firms are not. The m1, m2, and Sargan test show no indication of invalid IVs or unreliable estimates.

We now further investigate the degree of financial constraints of different types of firms within U.S. and China. For the case of China, four types of sample-splitting criteria are investigated: age, size, ownership type, and labor union existence. For U.S., only age and size are investgated.

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. Since the data set we use is a 10-year balanced panel, a firm classified as young (old) in any year would remain classified as that type across our sample period. The regressions based on firms classified as a constant type across our sample period is preferred since the results would be clearer for that type of firms. We will, therefore, adopt this type of classification through out our study. Table 2.4 and 2.5 report the results based on age-splitting for U.S. and China respectively. As can be seen in Table 2.5, young firms exhibit a much higher significant cash flow sensitivity than old firms in China, indicating they are relatively more financially constrained. Indeed, young firms are more likely to be riskier than large firms; the asymmetric information problem is also much more severe. On the other hand, large firms are usually stable and well-established. Investors and lenders are less reluctant to invest/lend to the firms; hence, they are less constrained. However, from Table 2.4, we found that both young and old firms in U.S. are unconstrained (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 publicly listed firms lasting for at least 10 consecutive years from 1998 to 2007. Again, the m1, m2, and Sargan test show no indication of invalid IVs or unreliable estimates.

Similar sample-splitting tests based on size can be seen in Table 2.6 and 2.7. We classify a firm as small (large) if its asset is below (above) the median asset in the annual asset distribution of all firms in every year. The results are pretty much the same 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 US. Again, asymmetric information problem plays a significant role in deterring funds from investors and banks to small firms in China, while no such problem exists for US due to their financial market development.

For sample-splitting regressions based on ownership type for China, we classify firms into six categories: SOEs (state-owned enterprises), COEs (collectively owned enterprises), DPEs (domestic private enterprises), HMTs (Hong Kong, Macau, and Taiwan enterprises), FIEs (foreign invested enterprises), and OTHERs (other types of firms), using information on 'ownership code' provided in our Chinese data set. A firm is classified as any type only if it has remained that type across our sample period. Results based on this ownership splitting are reported in Table 2.8. At one end, the cash flow coefficients in SOEs, COEs, FIEs, and OTHERs regressions are insignificantly different from zero, implying these types of firms do not experience any financial constraint. At the other end, DPEs have a highly significant cash flow coefficient of 0.339, reflecting a severe financial constraint they are facing, followed by HMTs with a coefficient of 0.214. In any regression, the m1, m2, and Sargan test again show no indication of invalid IVs or inappropriate estimation. As mentioned already, our results are sensible since SOEs and COEs are generally treated most generously by banks, while DPEs, on the other hand, should rank very low in the banks' hierarchy of lending. Meanwhile, in addition to the (possibly) favorable treatment by banks over DPEs, FIEs can rely on international financial markets or from intra-firm capital market of affiliated firms abroad, relaxing their financial constraint to some extent, and as found in our regression, they are actually not constrained at all. For HMTs, though classified as another group of foreign firms (similar to FIEs), their main source of capital is from Hong Kong, Macau and Taiwan: regions closely related to China. Hence, they can be viewed as a hybrid of DPEs and FIEs. As a result, their degree of financial constraint should be somewhere between that of DPEs and FIEs. This is confirmed in Table 2.8. Possibly smaller intra-firm capital market for HMTs compared to FIEs can be another explanation behind our findings, since most of the FIEs in China are parts of some big multinational corporations whereas HMTs are not. Finally, firms classified as OTHERs include cooperative units, joint ownership units, limited liability corporations and share-holding corporation. This type of firms is found to be financially unconstrained in our regression. We have no clear explanation for this findings as there are various kinds of firms classified in this type; they are included in our chapter for the sole purpose of covering all types of firms.

Last but not least, Table 2.9 reports the sample-splitting tests based on whether or not a firm has a labor union. In China, individual labor union has to be established within a firm, if a firm chooses to have a labor union. So the establishment of labor unions in China is similar to that in Western countries. However, the purpose is completely different. In Western countries, labor union helps workers bargain wages and working conditions with the firm. So it represents the interest of workers. In China, labor union never bargains with the firm, but passes on the ideology of the communist party to the workers and makes sure that this firm is politically correct or at least consistent with the communist party. It is in this sense having a labor union in the context of China can be taken as a proxy of having a political connection with the 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.

As can be seen from Table 2.9, even though both union and non-union firms exhibit significant cash flow sensitivities, the latter exhibits an observably higher sensitivity. The results indicate that both union and non-union firms are constrained; nevertheless, non-union firms are more constrained than union firms. Union firms are viewed as more politically connected than non-union firms, so that our results suggest political connection (using labor union as a proxy) can help alleviate firms' financial constraint. Again, the m1, m2, and Sargan tests in these regressions indicate no sign of IVs invalidity or unreliable estimates. 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 groups of non-SOEs. The results are reported in Table 2.10. Again, we see that non-SOEs union firms exhibit lower sensitivities than their counterparts. As a consequence, we conclude that political connection helps ease firm's financial constraint.

Finally, as mentioned from the beginning, our cross-sample comparisons will be misleading if cash flow acts as a proxy for omitted expected future profitability variables differently across samples. We investigate this issue directly by seeing if current or lagged cash flow variables forecast future sales growth or future cash flow differently across U.S. and China. Table 2.11 and 2.12 report the OLS estimates for these forecasting models. In table 2.11, although lagged cash flow does help to forecast future sales growth in China, its coefficient is rather small; moreover, the sum of the coefficients on both cash-flow terms is not noticeably significant, meaning that there seems to be no difference in predictive power of cash flow variable on sales growth rate across U.S. and China. A similar pattern arises for the cash flow forecasting models in Table 2.12. We have also investigated this issue in all our sample-splitting regressions, and found that cash-flow and lagged cash-flow terms do not vary much across our samples in each splitting criterion. These results re-assure us of the reliability of our interpretations we made earlier.

We conject the differences in degree of financial constraints by different groups of firms to different risk characteristics and degree of political connections. The data, indeed, supports our conjecture. As can be seen from Table 2.13 and 2.14, those more financially-constrained types of firms (young, small, DPEs, HMTs) are the ones with high risk and lower level of political connections on average compared to their counterparts (old, large, SOEs, COEs, FIEs, OTHERs).

Finally, we give the mean value of $y - k$ across different group of firms in Table 2.15. Calculating MRPK is a nontrivial matter, so instead, we use $y - k$ (average productivity of capital) to proxy for MRPK.[5] Table 2.15 suggests that there is a capital misallocation going on in China, due to difference in MRPK across different group of firms: younger, smaller, DPEs and less politically-connected firms have higher levels of capital productivity compared with their counterparts. Capital misallocation implies that these firms cannot take advantage of their high capital productivity by investing more, due to perhaps financial constraint reason. Indeed, our investment-cash flow sensitivities result supports this evidence: investment-cash flow sensitivity results show that younger, smaller, DPEs, and less politically-connected firms are the most contrained types of firms.

2.5 Conclusion

Although the lagged financial market is often being criticized to cause severe investment frictions in China, there have been relatively few researches testing which and why Chinese firms are in fact financially constrained. This chapter provides such a test by investigating the investment-cash flow sensitivities in an investment model under an error correction specification. Under

[5] A high value of $y - k$ means that for a fixed value of capital stock k, firm experiences high sales y, indicating it has a high capital productivity.

the null hypothesis of a perfect capital market, investment decision is independent of a firm's financial status. Therefore investment will not exhibit any sensitivity to cash flow when investment opportunities are properly controlled. Under the alternative, the imperfections in the capital market cause a wedge between the cost of internal and external finance. Therefore investment will respond positively to the availability of cash flow if a firm is financially constrained. Furthermore, a more constrained firm is likely to generate higher investment-cash flow sensitivities. As a benchmark, this model is applied to a panel of U.S. manufacturing firms from the Compustat, which shows no such sensitivity. In contrast, significant sensitivities are detected on a panel of Chinese manufacturing firms from the Chinese Industry Survey. These results simply indicate that Chinese firms face relatively more financial constraints than firms in U.S. Within U.S, we performs sample-splitting tests for young/old firms, and small/large firms. We found no differences in their cash flow sensitivities. Asymmetric information problems in the U.S seem to be eliminated or largely alleviated by its highly developed financial market. Within China, a hierarchy of sensitivities is found across firms with different age, size, ownership and political connection. A widely expected result is that young (small) Chinese firms are more constrained than old (large) Chinese firms. A more interesting result comes from ownership-splitting regressions. SOEs, COEs, FIEs and OTHERs are found to be unconstrained while DPEs are the most constrained, followed by HMTs. We also contributed additional empirical evidence that political connection helps relieve financial constraints faced by firms, using labor union existence as a proxy. Firms with labor union are, on average, less constrained than firms without labor union. This labor union existence (political connection), together with the risk level, within each firm are conjectured to be the reasons behind different degrees of financial constraint found across firms. Indeed, the data supports this conjecture. Those highly-constrained types of firms are the ones with high level of risks and low level of political connection on average. Finally, our results support the evidence that there is a capital misallocation in China, and that (young, small, DPEs, nonunion) firms cannot take advantage of their high capital productivity by investing more due to them being much financially constrained.

Though our chapter investigates why different types of firms have different degree of financial constraints, we didn't really distinguish and discuss in detail financial characteristics reason (for example in this chapter: risk) and policy distortion reason (for example in this chapter: union). Firms may experience high degree of financial constraints simply because they are high-risked firms or have other unfavorable financial characteristics viewed by banks and investors (and therefore, them being constrained is justified), or because they are treated unfavorably even though they are characteristically indifferent to other firms (policy distortion). Disentangling policy distortion from financial friction causes can be rather important to determine if capital misallcation problems can be alleviated by improving financial market (for example, to lower asymmetric information problem and therefore, improving lending/investing behavior) or by state-owned banks changing their lending attitudes (government intervention to lessen policy distortions).

2.6 Appendix A: Dynamic Panel Data Estimation

Dynamic panel data estimation is a relatively new econometric method, and has only recently been used more frequently. Therefore, we would like to devote lengthy pages to discuss in details how this method works. Notice that there are 2 types of estimators under this method: first-differenced GMM estimator, and system GMM estimator. Since our model uses only first-differenced GMM estimator introduced by Arellano and Bond (1991), and to avoid an even longer discussion of dynamic panel data method, we refer readers to Blundell and Bond (1998) for a detailed explanation on system GMM estimator.

Without loss of generality, a typical dynamic linear panel data model can be represented as:

$$y_{it} = \alpha y_{i,t-1} + \mathbf{x}_{it}\boldsymbol{\beta} + \eta_i + v_{it} \qquad |\alpha| < 1 \tag{2.9}$$

for $i = 1, ..., N$ and $t = 2, ...T$.

It is called 'dynamic' because the regression equation (2.9) contains lag dependent variables as regressors. Notice that the first observation is y_{i1}, so that the first available equation is $y_{i2} = \alpha y_{i1} + \mathbf{x}_{i2}\boldsymbol{\beta} + \eta_i + v_{i2}$, and we have $T - 1$ equations in 'levels'.

Two important properties of including the lagged dependent variable as regressors:

$$y_{i,t-1} = \alpha y_{i,t-2} + \mathbf{x}_{i,t-1}\boldsymbol{\beta} + \eta_i + v_{i,t-1} \tag{2.10}$$

1. $E\left(y_{i,t-1}\eta_i\right) > 0$

2. $E\left(y_{i,t-1}v_{i,t-1}\right) > 0$

$y_{i,t-1}$ is not strictly exogenous and the traditional OLS, within-groups, and first-differenced estimators, therefore, are inconsistent. First-differenced GMM method attempts to resolve this issue to generate consistent estimator for dynamic panel with large number of observations and finite time period.

Most of the estimation issues can be found in a simple dynamic model:

$$y_{it} = \alpha y_{i,t-1} + \eta_i + v_{it} \qquad |\alpha| < 1 \tag{2.11}$$

We will first characterize the properties of pooled OLS and within-groups estimators in this model.

OLS: Assuming $E\left(y_{i,t-1}v_{it}\right) = 0$, then $p\lim \widehat{\alpha}_{OLS} > \alpha$ as a result of the positive correlation between $y_{i,t-1}$ and η_i. OLS estimator is inconsistent, and is likely to be biased upwards.

Within-groups: Consider

$$\widetilde{y}_{i,t-1} = y_{i,t-1} - \frac{1}{T-1}\left(y_{i1} + ... + y_{i,T-1}\right) \tag{2.12}$$

and

$$\widetilde{v}_{it} = v_{it} - \frac{1}{T-1}\left(v_{i2} + ... + v_{iT}\right) \tag{2.13}$$

It can be shown that $E\left(\widetilde{y}_{i,t-1}\widetilde{v}_{it}\right) < 0$ and is of order $1/T$ (e.g. Nickell, 1981). As a result, $p\lim_{N\to\infty} \widehat{\alpha}_{WG} < \alpha$ for fixed T, i.e. the within-groups estimator is inconsistent, and is likely to be biased downwards.

Anderson-Hsiao 2SLS estimator To generate consistent estimator, generally, the model is first transformed to get rid of individual effect η_i, and then apply appropriate instrumental variables. Since within transformation introduces the shocks (v_{iT}) from all time periods into the transformed error term, it is not useful in this setting.

Instead, we should use first-differencing transformation.

$$\Delta y_{it} = \alpha \Delta y_{i,t-1} + \Delta v_{it} \tag{2.14}$$

for $i = 1, ..., N$ and $t = 3, ..., T$.

Because $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ and $\Delta v_{it} = v_{it} - v_{i,t-1}$, we get $E(\Delta y_{i,t-1} \Delta v_{it}) < 0$; first-differenced OLS estimator is inconsistent. Nevertheless, if we assume that $E(y_{i,t-1} v_{it}) = 0$, then $y_{i,t-2}$ (or $\Delta y_{i,t-2}$) is valid instrument for $\Delta y_{i,t-1}$ in equation (2.14). Two-stage least squares (2SLS) estimators were proposed by Anderson and Hsiao (1981):

$$\widehat{\boldsymbol{\alpha}}_{AH} = \left[\mathbf{\Delta y}_{-1}' \mathbf{Z} \left(\mathbf{Z}'\mathbf{Z}\right)^{-1} \mathbf{Z}' \mathbf{\Delta y}_{-1}\right]^{-1} \mathbf{\Delta y}_{-1}' \mathbf{Z} \left(\mathbf{Z}'\mathbf{Z}\right)^{-1} \mathbf{Z}' \mathbf{\Delta y} \tag{2.15}$$

where $\mathbf{\Delta y}$ is the stacked $N(T-2) \times 1$ vector of observations on Δy_{it}, $\mathbf{\Delta y}_{-1}$ is the stacked $N(T-2) \times 1$ vector of observations on $\Delta y_{i,t-1}$, and $\mathbf{Z}$ is the stacked $N(T-2) \times 1$ vector of observations on $y_{i,t-2}$. We will lose one more time series observation if $\Delta y_{i,t-2}$ is used as instrumental variable instead of $y_{i,t-2}$.

The Anderson-Hsiao 2SLS estimator is consistent as the number of observation $N \to \infty$, for fixed time period T. However, except in the case of $T = 3$, it is not efficient. When $T > 3$, further lagged variable of y_{it} and Δy_{it} (for example: y_{it-3} and/or Δy_{it-3}) are also valid instruments for first-differenced equations. We can improve its efficiency by utilizing these new instruments.

First-differenced GMM GMM (generalised method of moments) applies a set of orthogonality/moment conditions, and generate estimates (of the parameters) that can attain or resemble as closely as possible these moment conditions in the sample.

Let us return to our simple dynamic model

$$y_{it} = \alpha y_{i,t-1} + \eta_i + v_{it} \qquad |\alpha| < 1 \tag{2.16}$$

for $i = 1, ..., N$ and $t = 2, ..., T$.

Assumptions:

$$\text{Error components:} \quad E(\eta_i) = E(v_{it}) = E(\eta_i v_{it}) = 0 \tag{2.17}$$

$$\text{Serially uncorrelated shocks:} \quad E(v_{is} v_{it}) = 0 \text{ for } s \neq t \tag{2.18}$$

$$\text{Predetermined initial conditions:} \quad E(y_{i1} v_{it}) = 0 \text{ for } t = 2, ..., T \tag{2.19}$$

A number of moment conditions can be generated from these assumptions. More specifically, for the first-differenced equation (2.14), we have:

$$\begin{array}{cl} \text{First-differenced equations} & \text{Valid instruments} \\ (y_{i3} - y_{i2}) = \alpha (y_{i2} - y_{i1}) + (v_{i3} - v_{i2}) & y_{i1} \\ (y_{i4} - y_{i3}) = \alpha (y_{i3} - y_{i2}) + (v_{i4} - v_{i3}) & y_{i1}, y_{i2} \\ \vdots & \vdots \\ (y_{iT} - y_{i,T-1}) = \alpha (y_{i,T-1} - y_{i,T-2}) + (v_{iT} - v_{i,T-1}) & y_{i1}, y_{i2}, ..., y_{i,T-2} \end{array} \tag{2.20}$$

$E(y_{i1} \Delta v_{i3}) = 0$ because of our predetermined-initial-conditions assumption.

$E(y_{i1} \Delta v_{i4}) = 0$ because of similar reason.

$E(y_{i2} \Delta v_{i4}) = 0$ is achieved because $y_{i2} = \alpha y_{i1} + \eta_i + v_{i2}$, $E(\eta_i \Delta v_{i4}) = 0$ (error components assumption), and $E(v_{i2} \Delta v_{i4}) = 0$ (serially uncorrelated shocks).

We can provide similar reasoning to obtain the following $m = (T-2)(T-1)/2$ moment conditions

$$E(y_{i,t-s} \Delta v_{it}) = 0 \text{ for } t = 3, ..., T \text{ and } s \geq 2, \tag{2.21}$$

with the set of valid instruments provided in the table above.

These moment conditions can also be written as $E(Z_i' \Delta v_i) = 0$ where

$$Z_i = \begin{pmatrix} y_{i1} & 0 & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & y_{i1} & y_{i2} & \dots & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \dots & y_{i1} & y_{i2} & \dots & y_{i,T-2} \end{pmatrix} \text{ and } \Delta v_i = \begin{pmatrix} \Delta v_{i3} \\ \Delta v_{i4} \\ \vdots \\ \Delta v_{iT} \end{pmatrix} \tag{2.22}$$

where Z_i is a $(T-2) \times m$ matrix of instrumental variables, and Δv_i is a $(T-2) \times 1$ vector of first-differenced residuals.

Sample analogue

$$b_N(\alpha) = \frac{1}{N} \sum_{i=1}^{N} Z_i' \Delta v_i(\alpha) \tag{2.23}$$

For $T = 3$, we have 1 moment condition $E(y_{i1} \Delta v_{i3}) = 0$ and 1 parameter. α is just identified, the choice of the weight matrix is irrelevant, and the optimal GMM estimator coincides with the Anderson-Hsiao 2SLS estimator (using the level $y_{i,t-2}$ as the instrument).

For $T > 3$, we have $m > 1$ moment conditions. α is overidentified.

GMM estimators minimise a weighted quadratic distance

$$\begin{aligned}
\widehat{\alpha}_{GMM} &= \arg\min_{\alpha} J_N(\alpha) = b_N(\alpha)' W_N b_N(\alpha) \\
&= \arg\min_{\alpha} \left(\frac{1}{N} \sum_{i=1}^{N} \Delta v_i' Z_i \right) W_N \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' \Delta v_i \right) \\
&= \left(\Delta y_{-1}' Z W_N Z' \Delta y_{-1} \right)^{-1} \Delta y_{-1}' Z W_N Z' \Delta y \qquad (2.24)
\end{aligned}$$

where Δy and Δy_{-1} are the stacked $N(T-2) \times 1$ vectors of observations on Δy_{it} and $\Delta y_{i,t-1}$ as before, and $(Z = Z_1, ..., Z_N)'$ is the stacked $N(T-2) \times m$ matrix of observations on the instruments.

Comparing with

$$\widehat{\boldsymbol{\alpha}}_{AH} = \left[\boldsymbol{\Delta}\mathbf{y}_{-1}' \mathbf{Z} \left(\mathbf{Z}'\mathbf{Z} \right)^{-1} \mathbf{Z}' \boldsymbol{\Delta}\mathbf{y}_{-1} \right]^{-1} \boldsymbol{\Delta}\mathbf{y}_{-1}' \mathbf{Z} \left(\mathbf{Z}'\mathbf{Z} \right)^{-1} \mathbf{Z}' \boldsymbol{\Delta}\mathbf{y}, \tag{2.25}$$

greater (asymptotic) efficiency is achieved due to two reasons, for $T > 3$:

1- $\widehat{\alpha}_{GMM}$ utilizes more moment conditions ($m > 1$) than the Anderson-Hsiao 2SLS estimator.

2- Anderson-Hsiao 2SLS weighting matrix ($W_N = (Z'Z)^{-1} = \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' Z_i \right)^{-1}$) is not optimal.

GMM estimators $\widehat{\alpha}_{GMM}$ are shown to be very consistent (as $N \to \infty$) and normally-distributed asymptotically.

The optimal (two-step) GMM estimator sets

$$W_N = \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' \widehat{\Delta v_i} \widehat{\Delta v_i}' Z_i \right)^{-1} \tag{2.26}$$

giving

$$avar\left(\widehat{\alpha}_{GMM}\right) = N\left(\Delta y_{-1}' Z W_N Z' \Delta y_{-1}\right)^{-1} \tag{2.27}$$

For finite (small) sample, the variance of the two-step estimator as given above is not very accurate. More specifically, the (feasible) weighting matrix depends on an initial consistent estimator $\widehat{\alpha}$:

$$W_N\left(\widehat{\alpha}\right) = \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' \widehat{\Delta v_i}\left(\widehat{\alpha}\right) \widehat{\Delta v_i}\left(\widehat{\alpha}\right)' Z_i \right)^{-1}, \tag{2.28}$$

but not the true paramete value. As a result, there is some variation in $\widehat{\alpha}$, and in turn $W_N\left(\widehat{\alpha}\right)$, meaning that the GMM estimator

$$avar\left(\widehat{\alpha}_{GMM}\right) = N\left(\Delta y_{-1}' Z W_N\left(\widehat{\alpha}\right) Z' \Delta y_{-1}\right)^{-1} \tag{2.29}$$

is unreliable in finite (small) sample. The variation is trivial in very large sample, since the estimated parameter $\widehat{\alpha}$ converges to the true value.

Windmeijer (2005) proposes a finite sample correction that gives more accurate estimates of the variance of two-step GMM estimators. Econometric software, such as Stata, allows this correction to be implemented in its regression command. Inference based on this corrected variance are found to be reliable. We use this corrected version of estimated variance through out our chapter.

Weak instruments

The use of instrument variables (IV) regression is only useful when the instruments are informative for the endogenous regressors. In very large sample, as long as these instruments are correlated with the regressors, the resulting IV and GMM estimators would be consistent, reliable and have good sample properties. On the other hand, in small samples, though the estimators would still be consistent, the degree of correlation needs to be high enough (relative to the sample size) to make these estimators reliable. This small-sample issue is particularly pertinent for our dynamic GMM estimator when $\alpha \to 1$ in our simple model (2.16).

By analogy with randomwalks (innovations uncorrelated with past levels), the correlation between $\Delta y_{i,t-1}$ and the lagged levels $y_{i,t-s}$ for $s \geq 2$ becomes weaker as $\alpha \to 1$.

Recall our simple model

$$y_{it} = \alpha y_{i,t-1} + \eta_i + v_{it} \tag{2.30}$$

We can still indentify α as $\alpha \to 1$, and as long as $E\left(\eta_i^2\right) \neq 0$, the first-differenced GMM estimator is still consistent as $N \to \infty$.

When $\alpha = 1$, we get

$$\Delta y_{i,t-1} = \eta_i + v_{i,t-1} \text{ and } \Delta y_{i,t-2} = \eta_i + v_{i,t-2} \tag{2.31}$$

thus,

$$E\left(\Delta y_{i,t-1} \Delta y_{i,t-2}\right) = E\left(\eta_i^2\right) \neq 0 \tag{2.32}$$

Using $\Delta y_{i,t-2}$, for example, as instruments for $\Delta y_{i,t-1}$ is not completely uninformative, but evidence from Monte Carlo simulation suggests that first-differenced GMM would produce very imprecise and downward-biased estimators, especially when the values α is above 0.8.

Specification tests

Specifications tests of the form provided by Sargan (1958) and Hansen (1982) are usually employed for GMM estimators. These are the so-called overidentified-restrictions tests. GMM tries to make the moment conditions as close to 0 as possible, and in the case of just-identification, achieves these exactly. However in the case of overidentifying restrictions (more moment conditions that paramaters to be estimated), exactly-zero properties cannot be achieved for all moment conditions. These test statistics, therefore, test whether GMM can make these moment conditions very close to zero. If it can, the tests would not reject the null hypothesis of valid moment conditions and the GMM estimators are not unreliable. If it cannot, however, it simply means that not all the moment conditions are valid; GMM estimators would be inconsistent and unreliable. Sargan test and Hansen test follow χ^2 distributions, with degree of freedom equal to $J - K$, where J is the number of restrictions (moment conditions) and K the number of parameters to be estimated.

Direct test for serial correlation

The first-differenced GMM estimator described above is consistent conditioned on the serially-uncorrelated-shock assumption. A direct test for this assumption is proposed by Arellano and Bond (1991).

If the assumption $E\left(v_{is}v_{it}\right) = 0$, for $s \neq t$, is true, there would a negative correlation between $\Delta v_{it} = v_{it} - v_{i,t-1}$ and its lagged. The test of zero correlation between the first-differenced residuals and its lagged value is called an "m_1" test, and it should reject the null hypothesis of zero first-order correlation.

Δv_{it} would be uncorrelated with its second-lagged value Δv_{it-2}. The test of zero correlation between the first-differenced residuals and its second-lagged value is called an "m_2" test, and it should not reject the null hypothesis of zero second-order correlation. Under $H_0 : E\left(\Delta v_{it}\Delta v_{i,t-2}\right) = 0$, this m_2 test is calculated as

$$m_2 = \frac{\widehat{\Delta v}'_{-2}\widehat{\Delta v}_*}{se} \overset{a}{\sim} N\left(0,1\right) \tag{2.33}$$

where $\widehat{\Delta v}$ is the stacked $N\left(T-2\right) \times 1$ vector of first-differenced residuals $\widehat{\Delta v}_{it}$; $\widehat{\Delta v}_{-2}$ is the $N\left(T-4\right) \times 1$ vector of observations on the second lags of these first-differenced residuals $\widehat{\Delta v}_{i,t-2}$; $\widehat{\Delta v}_*$ is the $N\left(T-4\right) \times 1$ vector of observations on $\widehat{\Delta v}_{it}$ for the same periods in which $\widehat{\Delta v}_{i,t-2}$ is observed; se is the standard error of this autocovariance (se), given in Arellano and Bond (1991).

In short, for the serially-uncorrelated-shock assumption to apply, we need m_1 to produce negative test statistics and reject the null hypothesis of zero first-order correlation of first-differenced residuals, and m_2 to not reject the null hypothesis of zero second-order correlation of first-differenced residuals.

Table 2.1: Means (Standard Deviations) of Variables Used in Estimation

Variable	U.S.	China
I_t/K_{t-1}	0.185	0.107
	(0.269)	(0.251)
Δy_t	0.061	0.081
	(0.170)	(0.278)
$(k-y)_{t-2}$	-1.245	-0.683
	(0.698)	(1.029)
CF_t/K_{t-1}	0.323	0.196
	(0.571)	(0.259)

Table 2.2: AR(1) Models For $I/K, \Delta y, CF/K$, and $k - y$

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

Standard errors in parentheses

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.3: Error-Correction Models: First-Differenced GMM, t-2 Instruments

	U.S.	China
I_{t-1}/K_{t-2}	-0.276^{***}	-0.036^{*}
	(0.058)	(0.019)
Δy_t	0.560^{***}	0.078
	(0.085)	(0.052)
Δy_{t-1}	0.358^{***}	0.124^{***}
	(0.075)	(0.021)
$(k-y)_{t-2}$	-0.410^{***}	-0.117^{***}
	(0.074)	(0.022)
CF_t/K_{t-1}	-0.047	0.402^{***}
	(0.055)	(0.103)
CF_{t-1}/K_{t-2}	0.039	-0.074^{**}
	(0.025)	(0.035)
m1	0.000	0.000
m2	0.845	0.991
Sargan	0.360	0.065

Standard errors in parentheses

We report p-value for m1, m2 and Sargan tests.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.4: Error-Correction Models: Sample-Splitting Tests for U.S., Age, First-Differenced GMM, t-2 Instruments

	Young	Old
I_{t-1}/K_{t-2}	-0.370^{***}	-0.218^{***}
	(0.085)	(0.062)
Δy_t	0.562^{***}	0.597^{***}
	(0.100)	(0.086)
Δy_{t-1}	0.532^{***}	0.234^{***}
	(0.093)	(0.084)
$(k-y)_{t-2}$	-0.561^{***}	-0.295^{***}
	(0.102)	(0.085)
CF_t/K_{t-1}	-0.062	-0.033
	(0.047)	(0.067)
CF_{t-1}/K_{t-2}	0.015	0.081^{*}
	(0.023)	(0.046)
m1	0.000	0.000
m2	0.728	0.542
Sargan	0.389	0.606

Standard errors in parentheses

We report p-value for m1, m2 and Sargan tests.

${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$

Table 2.5: Error-Correction Models: Sample-Splitting Tests for China, Age, First-Differenced GMM, t-2 Instruments

	Young	Old
I_{t-1}/K_{t-2}	-0.056^{**}	-0.065^{**}
	(0.024)	(0.027)
Δy_t	0.097^{*}	0.169^{***}
	(0.058)	(0.062)
Δy_{t-1}	0.152^{***}	0.122^{***}
	(0.027)	(0.033)
$(k-y)_{t-2}$	-0.134^{***}	-0.139^{***}
	(0.028)	(0.033)
CF_t/K_{t-1}	0.307^{***}	0.200^{*}
	(0.110)	(0.113)
CF_{t-1}/K_{t-2}	-0.025	-0.076
	(0.038)	(0.048)
m1	0.000	0.000
m2	0.581	0.233
Sargan	0.038	0.263

Standard errors in parentheses

We report p-value for m1, m2 and Sargan tests.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.6: Error-Correction Models: Sample-Splitting Tests for US, Size, First-Differenced GMM, t-2 Instruments

	Small	Large
I_{t-1}/K_{t-2}	-0.296^{***}	-0.431^{***}
	(0.063)	(0.064)
Δy_t	0.477^{***}	0.632^{***}
	(0.087)	(0.098)
Δy_{t-1}	0.406^{***}	0.519^{***}
	(0.072)	(0.084)
$(k-y)_{t-2}$	-0.418^{***}	-0.615^{***}
	(0.072)	(0.085)
CF_t/K_{t-1}	0.046	−0.066
	(0.048)	(0.070)
CF_{t-1}/K_{t-2}	0.022	−0.019
	(0.028)	(0.050)
m1	0.000	0.000
m2	0.675	0.764
Sargan	0.550	0.427

Standard errors in parentheses

We report p-value for m1, m2 and Sargan tests.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.7: Error-Correction Models: Sample-Splitting Tests for China, Size, First-Differenced GMM, t-2 Instruments

	Small	Large
I_{t-1}/K_{t-2}	-0.046	-0.075^{***}
	(0.029)	(0.027)
Δy_t	0.175^{***}	0.139^{**}
	(0.066)	(0.060)
Δy_{t-1}	0.124^{***}	0.148^{***}
	(0.035)	(0.030)
$(k-y)_{t-2}$	-0.117^{***}	-0.151^{***}
	(0.036)	(0.030)
CF_t/K_{t-1}	0.456^{***}	0.090
	(0.129)	(0.128)
CF_{t-1}/K_{t-2}	-0.080^{*}	0.061
	(0.044)	(0.057)
m1	0.000	0.000
m2	0.718	0.912
Sargan	0.750	0.085

Standard errors in parentheses

We report p-value for m1, m2 and Sargan tests.

${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$

Table 2.8: Error-Correction Models: Sample-Splitting Tests for China, Ownership Type, First-Differenced GMM, t-2 Instruments

	SOEs	COEs	DPEs	HMTs	FIEs	OTHERs
I_{t-1}/K_{t-2}	-0.149^{**}	-0.181^{**}	-0.164^{***}	-0.023	-0.102^{***}	-0.120^{**}
	(0.060)	(0.072)	(0.059)	(0.032)	(0.040)	(0.050)
Δy_t	0.078	0.145^{**}	0.090	0.118^{***}	0.176^{***}	0.210^{***}
	(0.057)	(0.072)	(0.096)	(0.042)	(0.065)	(0.079)
Δy_{t-1}	0.176^{**}	0.166^{*}	0.279^{***}	0.107^{***}	0.203^{***}	0.232^{***}
	(0.070)	(0.090)	(0.077)	(0.038)	(0.040)	(0.061)
$(k-y)_{t-2}$	-0.196^{***}	-0.178^{**}	-0.244^{***}	-0.102^{**}	-0.192^{***}	-0.208^{***}
	(0.071)	(0.089)	(0.077)	(0.040)	(0.041)	(0.065)
CF_t/K_{t-1}	0.011	0.122	0.339^{**}	0.214^{**}	0.140	0.156
	(0.096)	(0.081)	(0.155)	(0.090)	(0.092)	(0.170)
CF_{t-1}/K_{t-2}	-0.0006	0.067	-0.005	-0.012	-0.021	0.043
	(0.047)	(0.052)	(0.113)	(0.034)	(0.052)	(0.089)
m1	0.000	0.000	0.000	0.000	0.000	0.000
m2	0.119	0.539	0.584	0.631	0.882	0.240
Sargan	0.705	0.429	0.162	0.187	0.143	0.396

Standard errors in parentheses

We report p-value for m1, m2 and Sargan tests.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.9: Error-Correction Models: Sample-Splitting Tests for China, Labor Union Existence, First-Differenced GMM, t-2 Instruments

	Non-Union	Union
I_{t-1}/K_{t-2}	-0.053^{*}	-0.060^{***}
	(0.032)	(0.021)
Δy_t	0.041	0.152^{***}
	(0.063)	(0.054)
Δy_{t-1}	0.164^{***}	0.134^{***}
	(0.037)	(0.024)
$(k-y)_{t-2}$	-0.147^{***}	-0.133^{***}
	(0.038)	(0.025)
CF_t/K_{t-1}	0.437^{***}	0.272^{***}
	(0.121)	(0.105)
CF_{t-1}/K_{t-2}	-0.043	-0.044
	(0.047)	(0.039)
m1	0.000	0.000
m2	0.960	0.774
Sargan	0.139	0.141

Standard errors in parentheses

We report p-value for m1, m2 and Sargan tests.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.10: Error-Correction Models: Sample-Splitting Tests for China, Labor Union Existence for Non-SOEs, First-Differenced GMM, t-2 Instruments

	Non-Union	Union
I_{t-1}/K_{t-2}	-0.041	-0.078^{***}
	(0.032)	(0.022)
Δy_t	0.026	0.191^{***}
	(0.063)	(0.056)
Δy_{t-1}	0.145^{***}	0.162^{***}
	(0.037)	(0.026)
$(k-y)_{t-2}$	-0.126^{***}	-0.158^{***}
	(0.038)	(0.026)
CF_t/K_{t-1}	0.439^{***}	0.200^{*}
	(0.118)	(0.106)
CF_{t-1}/K_{t-2}	-0.032	-0.029
	(0.046)	(0.040)
m1	0.000	0.000
m2	0.850	0.657
Sargan	0.232	0.081

Standard errors in parentheses

We report p-value for m1, m2 and Sargan tests.

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.11: Forecasting Models For Sales Growth–Dependent Variable Δy_t; OLS

	U.S.	China
I_{t-1}/K_{t-2}	0.077^{***}	0.079^{***}
	(0.017)	(0.006)
I_{t-2}/K_{t-3}	-0.036^{**}	0.057^{***}
	(0.014)	(0.005)
Δy_{t-1}	0.013	0.003
	(0.026)	(0.006)
Δy_{t-2}	-0.111^{***}	-0.003
	(0.023)	(0.005)
CF_{t-1}/K_{t-2}	-0.006	0.040^{***}
	(0.012)	(0.008)
CF_{t-2}/K_{t-3}	-0.011	-0.029^{***}
	(0.012)	(0.008)

Standard errors in parentheses

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.12: Forecasting Models For Cash Flow–Dependent Variable CF_t/K_{t-1}; OLS

	U.S.	China
I_{t-1}/K_{t-2}	-0.236^{***}	-0.104^{***}
	(0.031)	(0.004)
I_{t-2}/K_{t-3}	-0.113^{***}	-0.017^{***}
	(0.029)	(0.004)
Δy_{t-1}	0.127^{***}	0.070^{***}
	(0.047)	(0.004)
Δy_{t-2}	-0.129^{***}	0.021^{***}
	(0.043)	(0.003)
CF_{t-1}/K_{t-2}	0.368^{***}	0.516^{***}
	(0.040)	(0.010)
CF_{t-2}/K_{t-3}	0.151^{***}	0.226^{***}
	(0.035)	(0.009)

Standard errors in parentheses

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2.13: Risk and Union Characteristics for Young and Old Firms, China

	Young	Old	Small	Large
Percentage of firms who is high-risked	53.6%	46.3%	51.5%	44.4%
Percentage of firms who has a union	63.1%	79.8%	66.2%	79.4%

Table 2.14: Risk and Union Characteristics for Different Types of Ownership, China

	SOEs	COEs	DPEs	HMTs	FIEs	OTHERs
Percentage of firms who is high-risked	47.7%	48.2%	54.4%	55.8%	46.5%	46.2%
Percentage of firms who has a union	90.0%	68.5%	63.5%	55.1%	73.2%	86.3%

Table 2.15: Mean $y - k$, China

	$y - k$
Young	0.98
Old	0.43
Small	0.99
Large	0.42
SOEs	−0.19
COEs	0.72
DPEs	1.15
HMTs	0.84
FIEs	0.80
OTHERs	0.65
Non-Union	0.98
Union	0.61

Chapter 3

Policy Distortion and Financial Friction in Explaining Capital Misallocation in Chinese Manufacturing Industry

3.1 Introduction

Misallocation of capital is one of the most, if not the most, important factor in explaining differences between countries' total factor productivity (TFP), which in turn is a dominant factor affecting a country's GDP and GDP per capita. Understanding what causes misallocation of capital, therefore, is very significant for policy makers to design policy that can help improve the economy.

Capital misallocation exists when firms have different MRPK (marginal revenue product of capital). This difference in MRPK across firms can be due to financial friction or policy distortion. Financial friction (in capital misallocation) means that although a firm has a high MRPK compared to another firm, this firm cannot increase its capital investment to take advantage of its high MRPK at all, since it needs to raise the necessary fund externally, and since its financial status is viewed by potential investors or lenders as not very good. In a sense, with limited information in hand, investors and lenders justifiably raise the required rate of returns or interest rate for this firm: no discrimination or distortion exists along this line. Simply speaking, if it is the firm's (financial) characteristics that cause these difficulties in raising external funds, we call it financial friction. On the other hand, in some cases, even though two firms have identical financial status, they still receive different treatment with regard to rate of return or interest rate required by investors or lenders. We call this kind of distortion "policy distortion". For instance, in the case of China, SOEs (state-owned enterprises) seem to get a better treatment than DPEs (domestic private enterprises) by banks, many of which are state-owned, controlling for their financial status.

A recent study by Moll (2014) has shown that financial frictions are unimportant in explaining capital misallocation in the long run, due to self-financing process. Firms who have difficulties raising external finance will save up and accumulate sufficient internal funds to finance their desired investments. Most, if not all, countries are far away from this long run. Banerjee and Moll (2010) studies why misallocation persist. They conclude that though misallocation due to intensive margin should disappear asymptotically, misallocation on the extensive margin may persist. Similary, Midrigan and Xu (2014) evaluates the role of financial frictions in determining misallocation and TFP. They found relatively small losses from misallocation, but potentially large losses from low levels of entry and technology adoption. In contrast, Hsieh and Klenow (2009) found that there are sizable gaps in MRPKs across plants in China and India versus U.S, and that China can experience a TFP gain of about 30%-50% when there is a hypothetical relocation of capital and labor to equalize their marginal products to what is observed in the United States. Our chapter studies capital misallocation within existing firms in Chinese manufacturing industry and find a TFP loss of about 28.7%, in line with that of Hsieh and Klenow (2009). Though this study focuses only on internal margin, a sizeable capital misallocation and the corresponding huge TFP loss are not inconsistent with other literatures, since China is still transitioning itself towards to long run; as a result, the self-financing mechanism might not fully work in the case of China yet. In addition, our study also shows that apart from financial friction, policy distortion can also result in capital misallocation. So, capital misallocation on the intensive margin may still persist in the long-run even with self-financing mechanism fully at work.

The main focus of this chapter is to quantify the effect of policy distortion and financial friction in: 1. explaining the difference in MRPK (or user cost of capital) of SOEs, COEs, HMTs, FIEs, and MIXs relative to DPEs, and 2. TFP loss due to capital misallocation. Researchers have widely agreed that financial friction can cause capital misallocation, but only few papers have investigated the effect of policy distortion on capital misallocation, and more importantly, on TFP loss.[1] We aim to combine both effects together in a setup and quantify each effect using treatment-effect estimation. DPEs will be assigned a control group, whereas other ownerships are assigned treatments groups. We thought of the difference in ownership of firms as being due to a hidden policy or intervention, either by the firms themselves or by another party like government. The decision to be in one type of ownership may depend on the firm's financial status and other characteristics such as age, size, level of riskiness of the firm, level of pledgeability of firm's asset, firm's growth, and networth. The difference in MRPK between, let's say, SOEs and DPEs maybe due to these variables (called "financial friction") or due to other factors (called "policy distortion"). Due to potential bias arising from these confounding variables affecting firm's decision to be in one type of ownership than the other, propensity score matching (PSM) method is employed. PSM is useful in reducing this bias by selecting and comparing only those firms in control and treatment groups that have similar confounding variables. The effect we get after using PSM is basically "policy distortion" effect, where as the difference between the total effect (before PSM) and this policy distortion effect should be "financial friction".

We apply this PSM method to firms in Chinese manufacturing industries. Our benchmark results show that policy distortion accounts for about 60%, 60%, 200%, 300% and 130% in lowering user cost of capital respectively for SOEs, COEs, HMTs, FIEs and MIXs relative to DPEs, with the remaining percentage accounted for by financial frictions. What it means is that though SOEs are enjoying lower user cost of capital (lower MRPKs) than DPEs, only about 60% of this benefit is due to policy distortion. The remaining 40% is due to financial friction, i.e. because SOEs' financial status are healthier than DPEs', they should get preferable treatment from investors and lenders. The policy distortion effect of larger than 100%, like that

[1] One of them is Restuccia and Rogerson (2008), which shows that there is a sizeable reduction in output and TFP resulted from policies that create heterogeneity in the prices faced by individual producers.

of HMTs (200%), means that financial friction is working in favor of DPEs (100%), but due to a huge policy distortion prefering HMTs to DPEs (200%), the total effect is HMTs enjoying lower user cost of capital. We also find that the Chinese manufacturing industry as a whole would enjoy about 70% reduction in capital misallocation when no policy distortion exists. Furthermore, we establish that China is experiencing a TFP loss of about 28.7% per year over 2000-2007 with about 8.6% accounted for by financial frictions and the remaining 20.1% by policy distortions. Last but not least, we also investigate what factors contribute to the existence of policy distortion.

The rest of the chapter is organized as follows. Section 2 provides detailed reviews of propensity score matching, which will be employed in our chapter. Section 3 briefly describes the empirical model and data sets used. Section 4 provides and discusses our empirical results, together with some robustness checks. Section 5 concludes.

3.2 Propensity Score Matching

Propensity score matching is a method used in treatment-effect or program-evaluation study to derive the effectiveness of the program or policy given. Since propensity score matching method is not widely used and known, especially in financial economics, we will go through it in detail. Caliendo and Kopeinig (2008) provides a very good practical guidance for its implementation, and is referred to for most of our following discussion.

To understand why we need propensity score matching, first of all, notice that a fundamental problem related to each and every microeconomic evaluation study is the selection bias. Because we want to know the effectiveness of the program or policy given, what we need to compare is the difference in the outcome variable of the treated and the correpsonding outcome variable for the same individual were he/she is non-treated. But clearly, we can not observe both results at the same time for the same individual. Taking the outcome of non-participants (or controlled group) as an approximation of the outcome of the treated individual were he/she is non-treated (in the controlled) is not always the solution, since in general, participants (treated) and non-participants (controlled) are usually different, in other aspects. This 'selection bias' problem would arise if proper randomization is not achieved, for instance, in the case of a training program, motivated individuals, who are actively seeking for jobs and thus have a high chance of getting a job, tend to enroll themselves in the program. 'Matching' method is introduced to resolve this issue. More specifically, if there is a difference in a confounding variable x (a variable that can affect the outcome variable) in the treatment (T) and control (C) groups, then the difference in outcome variable y cannot be solely attributed to the difference in the treatment. One should compare only those observations in the controlled group that have the same value of x as the treated observations. The process of selecting observations from the controlled group with the same value of variable x as the treatment group like this is called 'matching'. After the observations are matched, the difference in outcome y can be regarded as the pure effect of treatment. Matching observations exactly along variable x, however, is infeasible or pretty difficult if x is a vector of confounding variables. 'Propensity score matching' is developed to address this problem.

The general framework in treatment-effect or program-evaluation study is the potential outcome approach (Roy, 1951, and Rubin, 1974). Let D_i be the treatment dummy variable ($D_i = 1$ for the treatment group and 0 for the controlled group), for each individual i. Let $Y_i\left(D_i\right)$ be the potential outcome variable (the variable intended to be affected by the program). What we are interested in is the treatment effect for an individual i:

$$Y_i(1) - Y_i(0) \tag{3.1}$$

This treatment effect, however, cannot be achieved practically because each individual i can be in either the treatment group or the controlled group, but not both, and therefore, we can either observe $Y_i(1)$ (if i is in the treatment group) or $Y_i(0)$ (if i is in the controlled group), but not both. The unobserved outcome is called counterfactual outcome.

Instead, 'average treatment effect on the treated' (ATT) is often used to. ATT is given by:

$$ATT = E[Y(1)|D = 1] - E[Y(0)|D = 1] \tag{3.2}$$

$E[Y(0)|D = 1]$ is the average outcome variable of those treatment-group observations were they are in the controlled group. Because this value is counterfactual, we have to find an appropriate estimate for it, to estimate ATT. An immediate response is to use $E[Y(0)|D = 0]$, the observed average outcome variable of those controlled-group observations, as an estimate. But this is not a proper solution (except in the case of randomized experiment) since observations in both groups generally have different characteristics (or confounding variables), meaning that even without the treatment (or program), we should observe different outcome between the two groups.

Re-write equation (3.2) as:

$$ATT = (E[Y(1)|D = 1] - E[Y(0)|D = 0]) - (E[Y(0)|D = 1] - E[Y(0)|D = 0]) \tag{3.3}$$

The first term on the right hand side of equation (3.3), $E[Y(1)|D = 1] - E[Y(0)|D = 0]$, is just the difference in average observed outcome for the treatment and controlled group. We call it 'average treatment effect' (ATE), and in practice, it can be computed directly from the data. The last term, $E[Y(0)|D = 1] - E[Y(0)|D = 0]$, is the difference in average outcome for observations in treatment and controlled group, in the abscence of the program. We call this 'self-selection bias' (SB). ATT, therefore, can be identified only if

$$E[Y(0)|D = 1] - E[Y(0)|D = 0] = 0 \tag{3.4}$$

In randomized experiment, where subjects are selected randomly into the treatment group, equation (3.4) is satisfied. However, in other evaluation or natural-experiment studies like ours, equation (3.4) would generally be violated; hence, matching methods are usually employed to resolve this selection bias problem.

There are two important assumptions imposed in matching methods.

1. **Conditional Independence Assumption (CIA)**: CIA assumes that

$$\text{(CIA)}\ Y(0), Y(1) \perp\!\!\!\perp D|X, \forall X \tag{3.5}$$

Simply speaking, this assumption means that conditional on the confounding variables X, observations in both treatment and controlled groups would have the same potential outcomes. In other words, if we are able to match observations in both groups along confounding variables X, we can use the observed outcome of one group as an estimate of the counterfactual outcome of the other. We assume that this assumption holds through out our chapter

Again, matching exactly along variables X is not achievable if X is of high dimensions (X contains more than one variable). Rosenbaum and Rubin (1983) propose a way to deal with this problem by matching observations according to some 'balancing score', a function of all variables X. 'Propensity score matching' is one type of this balancing score matching, where score is defind as the probability of being in the treatment group $P(D = 1|X) = P(X)$.

2. **Common Support Assumption**:

$$\text{(Common Support) } 0 < P(D = 1|X) < 1 \tag{3.6}$$

This assumption states that there is a non-zero probability of being in either the treatment or controlled group, for a given X. It ensures that we can find observations from the controlled group that can be matched to the observations in the treatment group.

Provided that CIA holds and that there are observations on common support, the propensity score matching (PSM) estimator for ATT is given as:

$$ATT = E_{P(X)|D=1}\{E[Y(1)|D = 1, P(X)] - E[Y(0)|D = 0, P(X)]\} \tag{3.7}$$

Simply speaking, ATT is calculated by first finding controlled-group observations (called counterfactual group) that can be matched to treatment-group observations using propensity score $P(X)$, then computing the difference in the average outcome between these two groups (treatment vs counterfactual groups).

The matching algorithm that we will use is "kernel" matching with common support. In kernel matching (KM), weighted average of matched observations in the control group is used to generate the counterfactual outcome. Applying kernel matching requires choosing kernel function and a bandwidth. DiNardo and Tobias (2001) find that the choice of kernel function is not significant in practice. The choice of bandwidth, however, can be much more important.[2] Large bandwidth can lead to a small variance but more biased estimate of true density function, and vice versa. Our chapter uses the default Epanechnikov kernel and the default bandwidth of 0.06 provided by Stata.

[2] See, for example, Silverman (1986), and Pagan and Ullah (1999), for more details.

Matching method is commonly used in health, labor, and international economics.[3] However, its application in financial economics is very few. We hope our study can also help encourage more usage of this method in financial economics research.

3.3 Empirical Implementation

3.3.1 Model

Based on the brief outline of the matching estimator in the general evaluation framework above, we are now ready to discuss the implementation of PSM in our chapter in detail.

We classified firms into different ownership types: SOEs, COEs, DPEs, HMTs, FIEs, and MIXs. We use DPEs as the control group, and SOEs, COEs, HMTs, FIEs, and OTHERs as treatment groups, one at a time. We match firms in control and treatment groups across "financial" variables such as: age, size, risk, pledgeability, growth and networth, using propensity score derived from probit models (if feasible, and logit, otherwise), with common support and kernel matching. More specifically, for any year t, we first run the following regression using probit model:

$$\begin{aligned}
\Pr(Treated_t &= 1|age_{t-1},\ size_{t-1},\ volatility_{t-1},\ pledge_{t-1},\ growth_{t-1},\ networth_{t-1}) = \\
&\Phi(\beta_0 + \beta_1 age_{t-1} + \beta_2 size_{t-1} + \beta_3 volatility_{t-1} + \beta_4 pledge_{t-1} \\
&+\beta_5 growth_{t-1} + \beta_6 networth_{t-1}) \qquad (3.8)
\end{aligned}$$

where Φ is the cumulative distribution function (CDF) of the standard normal distribution. Then, we calculate the "score" for each observation for both control and treatment groups, and match observations across these two groups using this score, with common support and kernel matching. Our outcome variable is $MRPK$ (marginal revenue product of capital). Appendix B details our precedure of backing out $MRPK$ from the data set for each firm.

We compare the average MRPKs (note that $MRPKs$ can be viewed as the user cost of capital as well, since firms will set $MRPKs$ equal to user cost of capital in optimizing their profits) between the two groups, before and after the matching. The difference between the

[3] See, for example, Lu et al. (2001), Lechner (2000), and Persson (2001)

average $MRPKs$ between control and treatment groups before matching (ATE) can be viewed as the difference in user cost of capital resulting from both financial frictions (due to financial variables above), and policy distortion (due to different ownerships). The difference between the average $MRPKs$ between control and treatment groups after matching (ATT) can be viewed as the difference in user cost of capital resulting from only policy distortion, since financial friction is already accounted for by matching observations across financial variables. The SB effect, which is the difference between ATE and ATT, would then be translated as the effect of financial frictions: the effect left after policy distortion must be financial friction, according to our setup.

The decision to use specifically these six variables (age, size, risk, pledgeability, growth and networth) as financial variables are based on existing literatures on the importance of different financial variables in affecting firm's user cost of capital (or $MRPK$) or degree of financial constraint: age and size (Hadlock and Pierce, 2010), risk and net worth (Stiglitz and Weiss, 1981), pledgeability (Almeida and Campello, 2007), and growth (Fazzari et al., 1988). We cannot say for sure that this set of variables completely covers the financial effect, but at least, they are the most intuitive and consistent with vast literature in this matter. Details on the variables used will be explained in later section.

3.3.2 Data

The data set used in our study is an annual firm-level 10-year balanced panel from Chinese Industry Survey (which the National Bureau of Statistics of China has conducted yearly since 1998) for China, covering the 1998-2007 period. The data, firm matching, and variables' construction are pretty much the same as what we have described in the previous chapter.

We focus only on manufacturing firms, defined by the 4-digit industrial code between 1300 (inclusive) and 4400. In contrast to Brandt et al (2012) who matches firm across different years using firm IDs, names, names of legal person representatives, phone number plus city code, and founding year plus geographic code plus industry code plus name of town plus name of main product, only firm IDs match is performed in our chapter (as we have some difficulties dealing with Chinese characters). As indicated in Brandt et al (2012) that about 96% of all their year-on-year matches are based on firm IDs, our resulting matched data set is still very highly comparable with theirs, and hopefully, of the true matched population. After this matching, we end up with an unbalanced panel of firms, with 130,103 firms in 1998 and 303,949 firms in 2007. Then, we clean the data by keeping firm-year with at least 8 employees (as those with less than 8 employees fall under a different legal regime, i.e. they are not legally considered as firms), positive sales, and positive book value of capital stock.

We deflate the revenue and profit using the GDP deflator from the China Statistical Yearbook. We construct our capital stock series using the following formula:

$$K_{it} = (1 - \delta) K_{i,t-1} + (BK_{it} - BK_{i,t-1}) / PI_{mt} \tag{3.9}$$

where BK_{it} is the book value of capital stock for firm i in year t; PI_{mt} is the price index of investment in fixed assets in year t constructed by Perkins and Rawski (2008); $\delta = 5\%$. The above formula is applied since the birthyear of a firm, where the initial real capital stock K_{i,t_0} is given by:

$$K_{i,t_0} = \frac{BK_{i,t_0}}{PI_{mt}} \tag{3.10}$$

where BK_{i,t_0} is the initial book value of capital stock when firm i was born in year t_0. For firm founded after 1998, this is simply the book value found in the data set for the birthyear. Otherwise, we preject BK_{i,t_0} to be:

$$BK_{i,t_0} = \frac{BK_{i,t_1}}{(1 + g_i)^{t_1 - t_0}} \tag{3.11}$$

where 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 two-digit industry capital stock growth rate of firm i from 1993 to t_1.

We construct real investment I_{it} as

$$I_{it} = (BK_{it} - BK_{i,t-1}) / PI_{mt} \tag{3.12}$$

when the initial data on book value of capital stock in year t and $t - 1$ are available.

We then delete those observations whose value of sales, book value of capital, or real capital stock is negative or zero. To avoid outliers, we replace the top and bottom 2.5% on year-by-year basis of: sales growth rate (*growth*), log capital over output ($k - y$), net tax over sale

($net\ tax/sale$), gross profit over output (GP/Y), and net worth over asset ($networth$). $Size$ is defined as the size of employment. The final 10-year balanced panel for the period 1998-2007 we obtain consists of 14,147 firms; equivalently, 141,470 firm-years. A firm is classified as SOEs, COEs, DPEs, HMTs or FIEs if its contributed capital from state, collective, domestic private, Hong Kong-Macau-Taiwan, or foreign party is more than 50% of firm's capital. Otherwise, we classify this firm as MIXs. There are 404 firm-years with missing value of contributed capital from at least one party; hence, we avoid classifying these firms as any ownership type. Table 3.1 shows the proportion of firms under each ownership across 1998-2007.

We would like to make an emphasis on the evolution of firm's ownership over time. The proportion (as well as the number) of SOEs and COEs firms have declined sharply from 1998 to 2007. In contrast, the number of DPEs firms (and MIXs) have increased dramatically. This pattern is mostly due to the privatization policy, "grasping the large and letting the small go" policy, adopted by the Chinese government as part of industrial reform in 1997.

Table 3.2 shows the mean values of our financial variables by ownership group.

3.4 Result

Table 3.3 gives an example of the result for probit regression that we use for the construction of "score" needed for matching purpose, when comparing SOEs and DPEs for year 2000.

To see if using propensity score matching really reduce the bias of the confounding variables, Table 3.4 reports the mean of these confounding variables before and after the matching, and the corresponding bias reduction and t-test of these biases. From Table 3.4, we see that all of the confounding variables have their mean difference between control (DPEs) and treatment groups (SOEs) reduced by at least 49%, and the p-value for the t-test that there is differences in the mean of these confounding variables increases a lot, from significant (below 0.05) to insignificant (above 0.05) in all cases. The same patterns for this bias reduction is observed in almost every treatment group across every year. This indicates that using PSM really allows us to purely look at the effect of policy distortion by adequately controlling for financial variables across treatment and controlled groups.

Next, we present the number of firms with common support for both control and treatment groups in Table 3.5. More specifically, we imposes a common support by dropping observations in the treatment group with propensity score higher than the maximum or less than the minimum propensity score of all the observations in the control group. In this sense, all observations in the control groups would be on support, but some observations for the treatment group might be off-support.

Table 3.6 gives the main result we are interested in. It shows the mean of $\ln(MRPK)$ (equivalently, user cost of capital) for both control (DPEs) and treatment groups (SOEs) before and after matching. Before matching, the difference between the mean of treatment and control groups can be attributed to 2 factors: financial frictions and policy distortion. After matching, because we have controlled for (or matched) the financial variables already by using PSM, the remaining difference between the two means can be attributed solely to policy distortion.

As we can see, the mean of $\ln(MRPK)$ for SOEs in 2000 is 0.623 lower than that of DPEs, meaning that SOEs are receiving favorable treatment (lower user cost of capital) than DPEs. This, like we mentioned, can be due to 2 reasons. First, SOEs might be doing better in terms of those financial variables mentioned; therefore, it is justiable for them to get treated more favorably. Second, apart from this financial frictions, policy distortion might also lower the user cost of capital of SOEs firms. To see if this is the case, we use PSM to match firms according to those financial variables, and look at the difference between the mean MRPKs across SOEs and DPEs. As can be seen from the second row of the result provided in Table 3.6, the mean MRPKs of SOEs is only 0.302 lower than that of DPEs. It means among the initial 0.623 lower of MRPKs of SOEs compared to DPEs, 0.302 is accounted for by policy distortion while the remaing 0.321 should be due to financial frictions. In other words, about 50% of the currently-observed favorable treatment of SOEs compared to DPEs is due to financial friction and the other 50% due to policy distortion.

The corresponding complete results for this policy distortion (ATT) and financial friction (SB), together with the total difference in $\ln(MRPK)$ for difference ownership group (ATE) across year 2000-2007 is given in Table 3.7. As expected, SOEs have the lowest user cost of capital, about 54% lower than DPEs on average, with 32% the result of favorable policy intervention and 22% the result of healthier financial characteristics. HMTs, FIEs, MIXs, and COEs also have lower user cost of capital, in descending order. If we look at HMTs and FIEs, they face a user cost of capital of 17% and 10% lower than DPEs, but this is driven totally by favorable policy treatment. Without any policy at play, HMTs and FIEs are in fact facing 18% and 20% higher user cost of capital than DPEs. But because policy favors HMTs and FIEs so much (lower their user cost by 36% and 30% compared to DPEs), the result is lower user cost of capital for them compared to DPEs. This is consistent with policy imposed by Chinese government to attract foreign direct investment (FDI) as they become a member of WTO in 2001. The "COMBINE" dataset is when we combine SOEs, COEs, HMTs, FIEs, and MIXs together. The results show that on average, non-DPE firms experience a 17% lower user cost of capital than DPEs, receive favorable policy treatment in order of 22% lower user cost of capital, and have 5% higher user cost of capital than DPEs based on their financial characteristics alone.

Table 3.8 gives the variance of $\ln MRPK$ and aggregate TFP loss. The first row is the variance of $\ln MRPK$, calculated using all firms. The second row is the variance of $\ln MRPK$ in the hypothetical economy, in which only the actual DPEs (the controlled group) and DPEs counterfactual to those treated observations exist. In other words, this hypothetical economy has unique ownership, which is DPE, and therefore, variation in $\ln MRPK$ in this hypothetical economy is soely due to financial friction. Under centain assumption (see, Midrigan and Xu, 2014), TFP loss is associated with capital misallocation through the following relationship:

$$\Delta \ln TFP_t = \frac{1}{2}\frac{\alpha\eta\left[1-(1-\alpha)\,\eta\right]}{1-\eta} var\left(\ln MRPK_{i,t}\right) \tag{3.13}$$

where α governs the share of capital in production, and η is the degree of returns to scale. Taking the standard values of $\alpha = 1/3$ and $\eta = 0.85$, we can find that TFP loss in the actual economy (first row) is about 28.7%. This TFP loss would reduce to only 8.6% in the hypothetical economy, i.e. financial friction causes TFP loss of only 8.6%. The difference, given in the third row, of 20.1% should be the result of policy distortion, provided that there is no model misspecification and no measurement error.

Next, we investigate what might be the reasons behind this policy distortion. We run a regression of the difference in $\ln MRPK$ between treated observations (SOEs, COEs, HMTs, FIEs, and MIXs combined) and counterfactual DPEs on net tax over sale ($net\ tax/sale$), export dummy ($EXPORT$), systematic risk beta ($beta$), labor union dummy ($LABORUNION$), western region dummy ($WESTERN$), and upstream-industry dummy ($UPSTREAM$). The result is given in Table 3.9.

Table 3.9 gives some interesting results about policy distortion. The coefficient on $net\ tax/sale$ is always positive significant, suggesting that firms that are treated badly in the product market (high tax) are also treated badly in the financial market (policy distortion). The coefficient on $EXPORT$ is always negative significant. This signifies that the Chinese government (large state-owned banks) gives favorable treatment to export-oriented firms, in an attempt to attract more FDI in China and opening up the economy following their WTO membership in 2001. The coefficient on $beta$, which denotes the systematic risk of firms, has a positive significant coefficient in early years (up to 2004) then become insignificant and negative significant in later years. Capital asset pricing model seems to be at work in early years (high risk, high required rate of return or user cost of capital), but not anymore in later years. One possible explanation is the change in risk-characteristics of the government (or state banks) over time. In the early years, government is pretty much concerned about employment; therefore, dissuade firms from undertaking risky project. In later years, when China is opening up its economy and trying to promote investment, the government might put more weight on investment, than on risk and employment. If this is the case, firm's investment which is considered risky and should not be undertaken previously, is encouraged to be undertaken now, by giving those firms lower user cost of capital. The coefficient on $LABORUNION$ is always negative significant. In Western countries, labor union helps workers bargain wages and working conditions with the firm. So it represents the interest of workers. In China, labor union never bargains with the firm, but passes on the ideology of the communist party to the workers and makes sure that this firm is politically correct or at least consistent with the communist party. It is in this sense having a labor union in the context of China can be taken as a proxy of having a political connection with the party. Negative significant coefficient on $LABORUNION$, therefore, signifies that polical connection can help lower user cost of capital. The coefficient on $WESTERN$ is always negative significant. This is accordant to the "Great Western Development Strategy" introduced in 2000, where government encourages firms to locate in western region by giving easy credit (lower user cost of capital). Finally, the coefficient on $UPSTREAM$ is always negative, but only significant in 3 of the 8 years studied. Negative coefficient is consistent with Li et al.

(2014), who found that upstream industry is typically monopolized by state-owned firms, and therefore, the favorable policy treatment should be expected; however, the results we found are not so strong in supporting this argument.

3.4.1 Robustness Check

We have use the year-by-year definition of ownership based on contributed capital to generate the results. This means we allow firms to change ownership type across years. As a robustness check, we will also use only those firms with constant ownership types, i.e. we do not allow firms to change ownerships. Two definition of constant ownerships are used: one based on 10-year definition (i.e. we required firms to remains in one ownership group through out 10 years, Table 3.10), another based on year-1998 and year-2007 definition (i.e. we only require firms to have the same ownership type in year 1998 and year 2007, Table 3.11). The results are both qualitatively and quantitatively similar. Additionally, we also use registered ownership to define ownership type (Table 3.12) and the results are the same. We use logarithm of total asset as proxy for size instead of employment (Table 3.13); use tangible asset over total asset as proxy for pledgeability (Table 3.14); use cash flow over capital as proxy for net worth (Table 3.15). All the results are pretty much similar both qualitatively and quantitatively. Finally, we use logarithm of sales over capital, $\ln Y_{it}/K_{it}$, instead of $\ln(MRPK_{it})$ as proxy for user cost of capital (Table 3.16), and the results are the same qualitatively, and pretty much similar quantitatively.

3.5 Conclusion

Capital misallocation can result in a huge loss of a country's productivity and growth. Capital misallocation exists when firms have different $MRPK$ (marginal revenue product of capital). This difference in MRPK across firms can be due to financial friction or policy distortion. Financial friction in capital misallocation means that although a firm has a high $MRPK$ compared to another firm, this firm cannot increase its capital investment to take advantage of its high $MRPK$ at all, since it needs to raise the necessary fund externally, and since its financial status is viewed by potential investors or lenders as not very good. In a sense, with limited information in hand, investors and lenders justifiably raise the required rate of returns or interest rate for this firm: no ex-ante discrimination or distortion exists along this line. On the other hand, in some cases, even though two firms have identical financial status, they still receive different treatment with regard to rate of return or interest rate required by investors or lenders. We call this kind of distortion "policy distortion". For instance, in the case of China, SOEs (state-owned enterprises) seem to get a better treatment than DPEs (domestic private enterprises) by banks, many of which are state-owned, controlling for their financial status. The main focus of this chapter is to quantify the effect of policy distortion and financial friction in: 1. explaining the difference in MRPK (or user cost of capital) of SOEs, COEs (collectively-owned enterprises), HMTs (Hong Kong, Macau and Taiwan enterprises), FIEs (foreign-invested enterprises), and MIXs (other types of firms) relative to DPEs, and 2. TFP loss due to capital misallocation. Our benchmark results show that policy distortion accounts for about 60%, 60%, 200%, 300% and 130% in lowering user cost of capital respectively for SOEs, COEs, HMTs, FIEs and MIXs relative to DPEs, with the remaining percentage accounted for by financial frictions. We also find that the Chinese manufacturing industry as a whole would enjoy about 70% reduction in capital misallocation when no policy distortion exists. We establish that China is experiencing a TFP loss of about 28.7% per year over 2000-2007 with about 8.6% accounted for by financial frictions and the remaining 20.1% by policy distortions. We also investigate what factors contribute to the existence of policy distortion and financial frictions.

This chapter is an empirical study aiming to directly investigate the effect of policy distortion and financial friction on firm's user cost of capital across ownership types in China. We have included variables that we think are the main driven force behind financial friction and policy distorion, but we understand that they might not fully govern the financial friction and policy distortion's effects. More research can be done by including additional variables deemed to be important factors in both mechanism. Finally, this is a within-country investigation. Future research on the relative importance of policy distortion across countries can give much insight on the relative inefficiency of governments in providing funds to firms, in affecting firm's investment, and in affecting its own total factor productivity and output.

3.6 Appendix B: Generating MRPK

We follow the approach proposed in Song and Wu (2015) to back out MRPK from ARPK.

Firm i in period t uses capital, labor and intermediate input, denoted by K_{it}, L_{it} and M_{it} respectively, to produce Q_{it} units of good i. The production technology exhibits constant returns to scale and takes a Cobb-Douglas form:

$$Q_{it} = A_{it} K_{it}^{\alpha_i} L_{it}^{\beta_i} M_{it}^{1-\alpha_i-\beta_i} \tag{3.14}$$

where A_{it} is stochastic, representing randomness in productivity; $\alpha_i > 0$ and $\beta_i > 0$ denote firm-specific capital and labor output elasticities respectively, $\alpha_i + \beta_i < 1$.

The firm sells its goods in a monopolistic product market, subject to an isoelastic downward-sloping demand curve,

$$Q_{it} = X_{it} P_{it}^{-\frac{1}{\eta_i}} \tag{3.15}$$

Here, X_{it} is stochastic, representing randomness in demand; P_{it} denotes the price of good i in period t, and $\eta_i \in (0,1)$ is the inverse of firm-specific demand elasticity.

From (3.14) and (3.15), sales revenue Y_{it}, given by $P_{it}Q_{it}$, is derived as:

$$Y_{it} = X_{it}^{\eta_i} A_{it}^{1-\eta_i} \left(K_{it}^{\alpha_i} L_{it}^{\beta_i} M_{it}^{1-\alpha_i-\beta_i} \right)^{1-\eta_i} \tag{3.16}$$

Denote w_{it} and m_{it} as wage rate and intermediate input price, respectively. For a given capital stock K_{it}, firm i chooses labor input L_{it} and intermediate input M_{it} to maximize its profits:

$$\Pi_{it} = \max_{L_{it}, M_{it}} \left(Y_{it} - w_{it} L_{it} - m_{it} M_{it} \right) \tag{3.17}$$

The first-order condition for this maximization implies:

$$\frac{\Pi_{it}}{Y_{it}} = \eta_i + \alpha_i (1 - \eta_i) \tag{3.18}$$

From (3.16), the marginal revenue product of capital ($MRPK$) is given by:

$$MRPK_{it} = \frac{\partial Y_{it}}{\partial K_{it}} = \alpha_i(1-\eta_i)\frac{Y_{it}}{K_{it}} \tag{3.19}$$

Taking natural logarithm on both sides of equation (3.19), and applying a second-order Taylor approximation, together with equation (3.18), we get:

$$\ln MRPK_{it} \approx \ln \frac{Y_{it}}{K_{it}} + \ln \frac{\Pi_{it}}{Y_{it}} - \eta_i \frac{Y_{it}}{\Pi_{it}} - \eta_i^2 \left(\frac{Y_{it}}{\Pi_{it}}\right)^2 \tag{3.20}$$

We, therefore, get an estimate of $MRPK_{it}$ as the residue from the following regression,

$$\ln \frac{Y_{it}}{K_{it}} = b_0 + b_1 \ln \frac{\Pi_{it}}{Y_{it}} + b_2 \frac{Y_{it}}{\Pi_{it}} + b_3 \left(\frac{Y_{it}}{\Pi_{it}}\right)^2 + b_4 CIC4_{it} + \epsilon_{it} \tag{3.21}$$

where $CIC4_{it}$ is the 4-digit industry dummy.

Table 3.1: Proportion of Firms under Each Ownership Group (%)

	SOE	COE	DPE	HMT	FIE	MIX
1998	18.2	21.0	16.0	14.9	13.0	17.0
1999	17.1	19.1	17.4	15.8	12.4	17.3
2000	15.3	17.9	20.4	15.5	12.3	18.7
2001	13.8	15.8	23.5	16.4	12.0	18.1
2002	13.1	14.2	25.7	15.8	12.6	18.7
2003	12.3	12.0	27.4	16.2	12.4	19.8
2004	10.6	11.3	28.3	15.7	12.8	21.3
2005	9.7	9.5	29.4	15.9	12.8	22.7
2006	8.9	9.2	29.6	16.1	12.6	23.6
2007	8.2	9.1	29.5	16.1	12.8	24.3

Note:
SOE: state-owned firms
COE: collective-owned firms
DPE: domestic private firms
HMT: Hong Kong, Macau and Taiwan owned firms
FIE: foreign invested firms
MIX: firms do not belong to any other five groups

Table 3.2: Mean Value of Firm Characteristics by Ownership Group

	age	size	volatility	pledge	growth	net worth
SOE	29	554	0.250	0.612	0.061	0.387
COE	19	292	0.255	0.625	0.084	0.392
DPE	18	279	0.256	0.614	0.097	0.389
HMT	11	557	0.268	0.621	0.056	0.509
FIE	10	546	0.250	0.623	0.077	0.522
MIX	18	408	0.260	0.621	0.087	0.423
Average	17	419	0.257	0.619	0.080	0.431

Note:
age: number of surviving years since birth
size: number of employees
volatility: volatility of real revenue growth rate
pledge: assets pledgeability defined following Berger et al. (1996)
growth: real revenue growth rate
net worth: (total assets - total liabilities)/total assets

Table 3.3: Results for Probit Regression

treated	Coeff.	Std. Err.	z	p>|z|
age1999	0.036	0.002	23.06	0.000
size1999	0.672	0.051	13.06	0.000
volatility1999	0.500	0.217	2.30	0.021
pledge1999	0.143	0.222	0.64	0.520
growth1999	-0.361	0.068	-5.28	0.000
networth1999	0.058	0.096	6.03	0.000
constant	-1.511	0.163	-9.26	0.000

Note:
Dependent variable: D = 1 (0) if ownership = SOE (DPE) in year 2000

Table 3.4: Mean Values of the Covariates Before and After the Matching

Variable	Sample	Mean Treated	Mean Control	% bias	% bias reduction	t-test t	p>|t|
age1999	Unmatched	25.393	13.514	90.4		29.64	0.000
	Matched	25.238	25.378	-1.1	98.8	-0.27	0.789
size1999	Unmatched	0.637	0.237	49.5		17.39	0.000
	Matched	0.553	0.533	2.5	94.9	0.82	0.412
volatility1999	Unmatched	0.239	0.257	-18.7		-5.94	0.000
	Matched	0.240	0.243	-3.3	82.2	-0.93	0.354
pledge1999	Unmatched	0.610	0.616	-7.0		-2.25	0.025
	Matched	0.610	0.607	3.5	50.2	1.00	0.318
growth1999	Unmatched	0.099	0.170	-24.3		-7.62	0.000
	Matched	0.100	0.098	0.6	97.4	0.19	0.847
networth1999	Unmatched	0.391	0.371	9.5		3.04	0.002
	Matched	0.391	0.381	4.8	49.0	1.40	0.161

Table 3.5: Summary for Number of Firms Off and On Support

Treatment Assignment	Common Support Off support	On support	Total
Untreated	0	2,558	2,558
Treated	19	1,649	1,668
Total	19	4,207	4,226

Table 3.6: Results for the ATE and the ATT

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
mrpk2000	Unmatched	-0.416	0.207	-0.623	0.025	-24.60
	ATT	-0.410	-0.108	-0.302	0.035	-8.62

Table 3.7: Summary of the Yearly Point Estimates for the ATE, ATT and the SB

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.62	-0.30	-0.32	-0.13	-0.06	-0.07	-0.27	-0.39	0.11	-0.18	-0.34	0.15	-0.12	-0.12	0.00	-0.25	-0.22	-0.03
2001	-0.57	-0.33	-0.24	-0.10	-0.07	-0.04	-0.22	-0.40	0.18	-0.14	-0.34	0.20	-0.13	-0.15	0.02	-0.22	-0.25	0.03
2002	-0.53	-0.32	-0.21	-0.08	*-0.05*	-0.03	-0.20	-0.41	0.21	-0.13	-0.35	0.22	-0.10	-0.13	0.03	-0.19	-0.24	0.05
2003	-0.58	-0.39	-0.19	-0.06	*-0.04*	-0.02	-0.15	-0.36	0.21	-0.08	-0.29	0.21	-0.06	-0.09	0.03	-0.17	-0.23	0.06
2004	-0.55	-0.33	-0.22	-0.04	*-0.02*	-0.02	-0.16	-0.36	0.20	-0.05	-0.26	0.21	-0.05	-0.08	0.03	-0.14	-0.20	0.06
2005	-0.54	-0.35	-0.19	-0.08	-0.06	-0.02	-0.15	-0.35	0.20	-0.09	-0.32	0.23	-0.07	-0.11	0.03	-0.15	-0.23	0.08
2006	-0.50	-0.30	-0.20	-0.07	-0.07	0.00	-0.12	-0.28	0.16	-0.05	-0.23	0.18	-0.06	-0.08	0.03	-0.12	-0.18	0.06
2007	-0.45	-0.28	-0.17	*-0.02*	*0.00*	-0.02	-0.11	-0.30	0.19	-0.08	-0.30	0.22	*-0.04*	-0.07	0.03	-0.10	-0.18	0.08
Avg	-0.54	-0.32	-0.22	-0.07	-0.04	-0.03	-0.17	-0.36	0.18	-0.10	-0.30	0.20	-0.08	-0.10	0.02	-0.17	-0.22	0.05

Note:
Control group is DPE.
Treatment group is SOE, COE, HMT, FIE and MIX, respectively.
COMBINE is the combined effect of the five evaluations using different treatment groups.
ATE: average treatment effect
ATT: average treatment effect on the treated
SB: selection bias, which is calculated as the difference between ATE and ATT
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates for ATE and ATT are statistically from zero at 5% significance level.

Table 3.8: Variance of Logrithm Marginal Revenue Products of Capital and Aggregate TFP Losses

	2000	2001	2002	2003	2004	2005	2006	2007	Average	TFP Loss
Var(mrpk)	0.702	0.694	0.695	0.683	0.688	0.696	0.713	0.741	0.701	0.287
Var(hy˙mrpk)	0.186	0.185	0.205	0.199	0.221	0.228	0.226	0.238	0.211	0.086
Difference	0.516	0.509	0.490	0.484	0.467	0.468	0.487	0.503	0.490	0.201

Table 3.9: Test on Possible Factors Underlying Policy Distortions

	2000	2001	2002	2003	2004	2005	2006	2007	Average
net tax/sale	0.175	0.188	0.161	0.162	0.169	0.170	0.159	0.152	0.167
EXPORT	-0.147	-0.171	-0.219	-0.178	-0.180	-0.157	-0.132	-0.156	-0.168
beta	0.032	0.019	0.005	0.030	0.019	*0.000*	-0.012	-0.026	0.010
LABORUNION	-0.078	-0.137	-0.135	-0.150	-0.094	-0.095	-0.129	-0.135	-0.119
WESTERN	-0.082	-0.131	-0.176	-0.156	-0.124	-0.144	-0.145	-0.160	-0.140
UPSTREAM	-0.037	*-0.021*	*-0.011*	*-0.023*	-0.047	*-0.016*	-0.038	*-0.030*	-0.041

Note:
Dependent variable is the difference between factual and counterfactual logMRPK of those treated firms.
Net tax is (tax-subsidies)/revenue.
EXPORT = 1 if a firm is an exporter.
UPSTREAM = 1 if a firm belongs to the upstream industries.
WESTERN = 1 if a firm locates in western China.
beta is risk of a firm proxied by the cyclicity of its revenue growth.
LABORUNION = 1 if a firm has a labor union.
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates are statistically from zero at 5% significance level.

Table 3.10: Summary of the Yearly Point Estimates for the ATE, ATT and the SB (10-year definition)

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.78	-0.36	-0.42	-0.29	-0.13	-0.16	-0.31	-0.45	0.14	-0.16	-0.33	0.17	-0.23	-0.26	0.04	-0.35	-0.33	-0.02
2001	-0.73	-0.39	-0.35	-0.25	-0.14	-0.11	-0.29	-0.44	0.14	-0.17	-0.32	0.15	-0.22	-0.25	0.03	-0.33	-0.33	0.00
2002	-0.72	-0.44	-0.28	-0.21	-0.15	-0.05	-0.23	-0.38	0.14	-0.17	-0.34	0.17	-0.20	-0.25	0.05	-0.31	-0.33	0.03
2003	-0.73	-0.46	-0.27	-0.22	-0.13	-0.10	-0.22	-0.38	0.16	-0.11	-0.30	0.19	-0.16	-0.17	0.01	-0.28	-0.32	0.03
2004	-0.73	-0.48	-0.25	-0.21	-0.14	-0.07	-0.25	-0.39	0.14	-0.12	-0.30	0.19	-0.16	-0.17	0.01	-0.29	-0.32	0.03
2005	-0.71	-0.53	-0.17	-0.13	-0.09	-0.05	-0.24	-0.39	0.14	-0.15	-0.37	0.22	-0.17	-0.21	0.04	-0.29	-0.35	0.07
2006	-0.62	-0.42	-0.20	-0.14	-0.11	-0.03	-0.17	-0.34	0.16	-0.10	-0.32	0.21	-0.18	-0.20	0.02	-0.24	-0.30	0.07
2007	-0.60	-0.41	-0.19	-0.17	-0.10	-0.07	-0.21	-0.37	0.15	-0.16	-0.36	0.19	-0.10	-0.14	0.04	-0.25	-0.31	0.06
Avg	-0.70	-0.44	-0.27	-0.20	-0.12	-0.08	-0.24	-0.39	0.15	-0.14	-0.33	0.19	-0.18	-0.21	0.03	-0.29	-0.33	0.03

Note:
Control group is DPE.
Treatment group is SOE, COE, HMT, FIE and MIX, respectively.
COMBINE is the combined effect of the five evaluations using different treatment groups.
ATE: average treatment effect
ATT: average treatment effect on the treated
SB: selection bias, which is calculated as the difference between ATE and ATT
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates for ATE and ATT are statistically from zero at 5% significance level.

Table 3.11: Summary of the Yearly Point Estimates for the ATE, ATT and the SB (Year1998-Year2007 definition)

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.76	-0.37	-0.39	-0.26	-0.13	-0.13	-0.36	-0.46	0.10	-0.20	-0.33	0.14	-0.13	-0.14	0.01	-0.33	-0.30	-0.02
2001	-0.70	-0.35	-0.35	-0.22	-0.10	-0.12	-0.32	-0.43	0.11	-0.18	-0.33	0.15	-0.13	-0.12	-0.01	-0.30	-0.29	-0.01
2002	-0.71	-0.42	-0.29	-0.19	-0.12	-0.07	-0.29	-0.43	0.14	-0.18	-0.33	0.15	-0.13	-0.15	0.02	-0.28	-0.30	0.02
2003	-0.72	-0.45	-0.27	-0.18	-0.08	-0.10	-0.24	-0.37	0.13	-0.12	-0.27	0.15	-0.11	-0.11	0.00	-0.25	-0.27	0.01
2004	-0.72	-0.45	-0.26	-0.19	-0.13	-0.06	-0.26	-0.37	0.11	-0.13	-0.27	0.14	-0.12	-0.12	0.00	-0.26	-0.28	0.01
2005	-0.68	-0.48	-0.21	-0.13	-0.08	-0.05	-0.24	-0.36	0.12	-0.15	-0.31	0.16	-0.14	-0.16	0.02	-0.25	-0.29	0.04
2006	-0.60	-0.37	-0.23	-0.12	-0.09	-0.02	-0.20	-0.30	0.10	-0.11	-0.24	0.13	-0.11	-0.11	0.00	-0.21	-0.23	0.02
2007	-0.59	-0.39	-0.19	-0.10	-0.03	-0.07	-0.21	-0.31	0.10	-0.16	-0.27	0.11	-0.08	-0.10	0.02	-0.21	-0.23	0.02
Avg	-0.68	-0.41	-0.27	-0.17	-0.09	-0.08	-0.26	-0.38	0.12	-0.15	-0.30	0.14	-0.12	-0.13	0.01	-0.26	-0.27	0.01

Note:
Control group is DPE.
Treatment group is SOE, COE, HMT, FIE and MIX, respectively.
COMBINE is the combined effect of the five evaluations using different treatment groups.
ATE: average treatment effect
ATT: average treatment effect on the treated
SB: selection bias, which is calculated as the difference between ATE and ATT
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates for ATE and ATT are statistically from zero at 5% significance level.

Table 3.12: Summary of the Yearly Point Estimates for the ATE, ATT and the SB (Registered ownership)

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.80	-0.35	-0.45	-0.16	-0.02	-0.14	-0.31	-0.34	0.03	-0.19	-0.25	0.06	-0.25	-0.06	-0.20	-0.31	-0.19	-0.12
2001	-0.74	-0.35	-0.39	-0.16	-0.06	-0.11	-0.26	-0.36	0.09	-0.18	-0.29	0.12	-0.26	-0.10	-0.16	-0.29	-0.23	-0.06
2002	-0.70	-0.28	-0.42	-0.09	-0.01	-0.08	-0.23	-0.37	0.13	-0.15	-0.31	0.15	-0.23	-0.06	-0.17	-0.25	-0.21	-0.05
2003	-0.73	-0.38	-0.36	-0.09	-0.03	-0.06	-0.22	-0.35	0.14	-0.12	-0.28	0.15	-0.25	-0.10	-0.15	-0.25	-0.23	-0.02
2004	-0.69	-0.41	-0.27	-0.08	-0.03	-0.05	-0.18	-0.33	0.14	-0.09	-0.26	0.16	-0.20	-0.10	-0.10	-0.21	-0.22	0.01
2005	-0.69	-0.44	-0.25	-0.07	-0.05	-0.01	-0.17	-0.30	0.14	-0.13	-0.30	0.17	-0.22	-0.13	-0.09	-0.22	-0.24	0.02
2006	-0.59	-0.30	-0.29	-0.05	-0.04	0.00	-0.15	-0.29	0.14	-0.09	-0.26	0.17	-0.21	-0.13	-0.08	-0.19	-0.21	0.02
2007	-0.59	-0.34	-0.24	-0.03	-0.02	-0.01	-0.16	-0.31	0.16	-0.13	-0.32	0.19	-0.22	-0.14	-0.08	-0.20	-0.24	0.04
Avg	-0.69	-0.36	-0.33	-0.09	-0.03	-0.06	-0.21	-0.33	0.12	-0.14	-0.28	0.15	-0.23	-0.10	-0.13	-0.24	-0.22	-0.02

Note:
Control group is DPE.
Treatment group is SOE, COE, HMT, FIE and MIX, respectively.
COMBINE is the combined effect of the five evaluations using different treatment groups.
ATE: average treatment effect
ATT: average treatment effect on the treated
SB: selection bias, which is calculated as the difference between ATE and ATT
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates for ATE and ATT are statistically from zero at 5% significance level.

Table 3.13: Summary of the Yearly Point Estimates for the ATE, ATT and the SB (Size=Logarithm Total Asset)

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.62	-0.27	-0.35	-0.13	-0.05	-0.07	-0.27	-0.30	0.03	-0.18	-0.21	0.03	-0.12	-0.07	-0.05	-0.25	-0.17	-0.08
2001	-0.57	-0.29	-0.28	-0.10	-0.07	-0.04	-0.22	-0.33	0.11	-0.14	-0.23	0.09	-0.13	-0.10	-0.03	-0.22	-0.19	-0.03
2002	-0.53	-0.27	-0.26	-0.08	-0.05	-0.03	-0.20	-0.33	0.13	-0.13	-0.25	0.12	-0.10	-0.08	-0.01	-0.19	-0.19	-0.01
2003	-0.58	-0.38	-0.20	-0.06	-0.05	-0.02	-0.15	-0.29	0.14	-0.08	-0.21	0.13	-0.06	-0.05	-0.01	-0.17	-0.18	0.02
2004	-0.55	-0.35	-0.21	-0.04	-0.03	-0.01	-0.16	-0.31	0.15	-0.05	-0.17	0.12	-0.05	-0.05	0.00	-0.14	-0.16	0.02
2005	-0.54	-0.36	-0.18	-0.08	-0.06	-0.02	-0.15	-0.31	0.16	-0.09	-0.26	0.17	-0.07	-0.09	0.02	-0.15	-0.20	0.05
2006	-0.50	-0.31	-0.19	-0.07	-0.07	0.00	-0.12	-0.24	0.11	-0.05	-0.16	0.10	-0.06	-0.07	0.01	-0.12	-0.15	0.03
2007	-0.45	-0.27	-0.18	-0.02	0.00	-0.02	-0.11	-0.27	0.17	-0.08	-0.25	0.18	-0.04	-0.06	0.02	-0.10	-0.16	0.06
Avg	-0.54	-0.31	-0.23	-0.07	-0.05	-0.03	-0.17	-0.30	0.12	-0.10	-0.22	0.12	-0.08	-0.07	-0.01	-0.17	-0.18	0.01

Note:
Control group is DPE.
Treatment group is SOE, COE, HMT, FIE and MIX, respectively.
COMBINE is the combined effect of the five evaluations using different treatment groups.
ATE: average treatment effect
ATT: average treatment effect on the treated
SB: selection bias, which is calculated as the difference between ATE and ATT
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates for ATE and ATT are statistically from zero at 5% significance level.

Table 3.14: Summary of the Yearly Point Estimates for the ATE, ATT and the SB (Pledgeability=Tangible Asset/Total Asset)

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.63	-0.31	-0.32	-0.13	-0.03	-0.09	-0.28	-0.41	0.12	-0.19	-0.36	0.17	-0.12	-0.12	-0.01	-0.26	-0.23	-0.03
2001	-0.57	-0.32	-0.25	-0.10	-0.05	-0.05	-0.23	-0.41	0.17	-0.15	-0.33	0.18	-0.13	-0.14	0.01	-0.22	-0.24	0.01
2002	-0.54	-0.31	-0.23	-0.09	-0.04	-0.05	-0.22	-0.41	0.19	-0.15	-0.34	0.19	-0.10	-0.11	0.01	-0.20	-0.23	0.03
2003	-0.59	-0.38	-0.21	-0.07	-0.04	-0.04	-0.17	-0.36	0.19	-0.09	-0.29	0.20	-0.07	-0.09	0.01	-0.18	-0.22	0.05
2004	-0.55	-0.33	-0.23	-0.04	-0.01	-0.03	-0.16	-0.34	0.18	-0.05	-0.25	0.20	-0.05	-0.07	0.02	-0.14	-0.19	0.05
2005	-0.54	-0.35	-0.20	-0.08	-0.06	-0.02	-0.16	-0.36	0.19	-0.11	-0.32	0.21	-0.08	-0.11	0.03	-0.16	-0.23	0.07
2006	-0.51	-0.29	-0.22	-0.07	-0.08	0.01	-0.14	-0.27	0.14	-0.07	-0.22	0.15	-0.06	-0.08	0.01	-0.13	-0.18	0.04
2007	-0.47	-0.27	-0.19	-0.03	-0.01	-0.02	-0.13	-0.30	0.17	-0.10	-0.29	0.19	-0.05	-0.07	0.02	-0.12	-0.18	0.06
Avg	-0.55	-0.32	-0.23	-0.08	-0.04	-0.04	-0.19	-0.36	0.17	-0.11	-0.30	0.19	-0.08	-0.10	0.01	-0.18	-0.21	0.03

Note:
Control group is DPE.
Treatment group is SOE, COE, HMT, FIE and MIX, respectively.
COMBINE is the combined effect of the five evaluations using different treatment groups.
ATE: average treatment effect
ATT: average treatment effect on the treated
SB: selection bias, which is calculated as the difference between ATE and ATT
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates for ATE and ATT are statistically from zero at 5% significance level.

Table 3.15: Summary of the Yearly Point Estimates for the ATE, ATT and the SB (Net worth=Cash Flow/Capital)

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.63	-0.25	-0.38	-0.13	-0.06	-0.07	-0.30	-0.36	0.06	-0.21	-0.35	0.14	-0.12	-0.12	0.00	-0.26	-0.21	-0.05
2001	-0.59	-0.28	-0.30	-0.12	-0.09	-0.03	-0.24	-0.33	0.09	-0.17	-0.36	0.19	-0.14	-0.15	0.01	-0.24	-0.23	-0.01
2002	-0.56	-0.27	-0.29	-0.09	-0.05	-0.04	-0.23	-0.34	0.11	-0.17	-0.36	0.18	-0.10	-0.12	0.01	-0.22	-0.22	0.00
2003	-0.57	-0.29	-0.28	-0.08	-0.06	-0.03	-0.17	-0.30	0.14	-0.12	-0.32	0.19	-0.07	-0.10	0.03	-0.18	-0.21	0.02
2004	-0.56	-0.23	-0.33	-0.07	-0.06	-0.01	-0.18	-0.31	0.13	-0.11	-0.31	0.20	-0.06	-0.09	0.03	-0.17	-0.19	0.03
2005	-0.55	-0.23	-0.32	-0.12	-0.08	-0.04	-0.16	-0.29	0.13	-0.14	-0.33	0.19	-0.08	-0.11	0.03	-0.17	-0.20	0.03
2006	-0.51	-0.18	-0.33	-0.11	-0.09	-0.02	-0.15	-0.24	0.09	-0.10	-0.26	0.16	-0.07	-0.07	0.01	-0.15	-0.16	0.01
2007	-0.47	-0.14	-0.33	-0.06	-0.03	-0.04	-0.11	-0.22	0.11	-0.10	-0.27	0.17	-0.04	-0.04	0.00	-0.12	-0.14	0.02
Avg	-0.55	-0.23	-0.32	-0.10	-0.06	-0.03	-0.19	-0.30	0.11	-0.14	-0.32	0.18	-0.08	-0.10	0.02	-0.19	-0.19	0.01

Note:
Control group is DPE.
Treatment group is SOE, COE, HMT, FIE and MIX, respectively.
COMBINE is the combined effect of the five evaluations using different treatment groups.
ATE: average treatment effect
ATT: average treatment effect on the treated
SB: selection bias, which is calculated as the difference between ATE and ATT
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates for ATE and ATT are statistically from zero at 5% significance level.

Table 3.16: Summary of the Yearly Point Estimates for the ATE, ATT and the SB (Log(Sales/Capital) instead of Log(MRPK))

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-1.05	-0.55	-0.51	-0.21	-0.10	-0.11	-0.13	-0.31	0.19	-0.22	-0.44	0.22	-0.23	-0.23	0.00	-0.35	-0.31	-0.05
2001	-0.99	-0.58	-0.40	-0.21	-0.14	-0.07	-0.10	-0.36	0.25	-0.19	-0.46	0.27	-0.24	-0.25	0.02	-0.32	-0.34	0.02
2002	-0.90	-0.57	-0.33	-0.16	-0.11	-0.05	-0.10	-0.40	0.30	-0.17	-0.47	0.29	-0.18	-0.22	0.04	-0.28	-0.34	0.06
2003	-0.90	-0.61	-0.29	-0.13	-0.10	-0.03	-0.04	-0.33	0.29	-0.10	-0.39	0.28	-0.14	-0.17	0.03	-0.23	-0.30	0.07
2004	-0.83	-0.52	-0.31	-0.09	-0.06	-0.03	-0.04	-0.31	0.27	-0.05	-0.33	0.29	-0.12	-0.16	0.04	-0.18	-0.26	0.08
2005	-0.82	-0.54	-0.27	-0.17	-0.14	-0.03	-0.05	-0.31	0.26	-0.09	-0.37	0.28	-0.16	-0.21	0.04	-0.21	-0.29	0.09
2006	-0.78	-0.51	-0.27	-0.14	-0.13	-0.01	-0.05	-0.28	0.22	-0.08	-0.32	0.24	-0.13	-0.16	0.03	-0.18	-0.25	0.08
2007	-0.71	-0.47	-0.25	-0.07	-0.05	-0.02	-0.06	-0.31	0.25	-0.07	-0.35	0.28	-0.10	-0.14	0.04	-0.14	-0.24	0.09
Avg	-0.87	-0.54	-0.33	-0.15	-0.10	-0.04	-0.07	-0.32	0.25	-0.12	-0.39	0.27	-0.16	-0.19	0.03	-0.24	-0.29	0.05

Note:
Control group is DPE.
Treatment group is SOE, COE, HMT, FIE and MIX, respectively.
COMBINE is the combined effect of the five evaluations using different treatment groups.
ATE: average treatment effect
ATT: average treatment effect on the treated
SB: selection bias, which is calculated as the difference between ATE and ATT
Average is the value of estimates averaged across years.
Estimates in Italic are not statistically different from zero at 5% significance level.
All other estimates for ATE and ATT are statistically from zero at 5% significance level.

Chapter 4

Financial Constraint and Firm's Productivity

4.1 Introduction

More and more literature has found that developed financial system can help ease information processing of firms, reduce costs of transaction, mobilize and pool savings, and ease the exchange of goods and services; thereby, it is able to promote savings, investment and economic growth for the country as a whole.[1] At micro-level, it has been shown that finance can affect firm's real investment (Fazzari et al., 1988) and employment (Nickell and Nicolitsas, 1999), the two main factors of production.

A large number of empirical researches have shown that cross-country differences in GDP per capita are not due to factor accumulation, but largely and mostly accounted for by differences in total factor productivity (TFP). At macro-level, because undeveloped countries have poorer financial system than developed countries, numerous researches have tried to investigate if financial development plays a significant role in increasing the aggregate TFP. At micro-level, therefore, it is important to examine if finance stimulates TFP and economic growth by directly nurturing firm-level productivity. There are several channels through which finance can promote firm productivity: by promoting R&D (Brown et al, 2009), encouraging more technology

[1] See Levine (2005) for a survey.

adoption (Ayyagari et al, 2011), inducing more investment (Fazzari et al, 1988) and allowing firms to produce higher quality goods (Fan et al, 2015).

Even though the relationship between finance and firm productivity is a significant topic in economics, there have been relatively few studies in this literature. Among these few studies are Nucci et al. (2005), Gatti and Love (2008), Moreno-Badia and Slootmaeketrs (2009), and Chen and Guariglia (2013) for studies based on Italian, Bulgarian, Estonian, and Chinese firms, respectively.

This chapter attempts to fill in this gap, by studying the effect of finance (or financial constraint) on firm productivity using a large panel of Chinese manufacturing firms. Although China has a relatively undeveloped financial market, China has been enjoying a very high GDP growth for the last few decades (Allen et al., 2005; Guariglia et al., 2011). Most of this growth has been attributed to the increase in productivity (Brandt et al., 2012; Zheng et al., 2009; Guariglia et al., 2011). Therefore, it is interesting to see if this productivity growth stems from financial development, or if finance plays no role at all in promoting growth.

Our main contribution is the use of more rigorous and reliable techniques in studying the effect of financial constraint on productivity. More specifically, we estimate productivity using ACF (Akerberg, Caves and Frazer, 2006) production-function-estimation approach by directly incorporating our measure of financial constraint directly into the 2nd-stage regression (the equation of motion of productivity). This method will produce consistent estimators of all inputs' parameters; hence, productivity. Ignoring the effect of financial constraint in estimating the production function parameters will lead to biased and inconsistent estimators (and productivity) if financial constraint is an important determinant of productivity. Our study, by incorporating the effect of financial variable on productivity directly in this way, is inspired by De Loecker and Warzynski (2012) and De Loecker (2013). To our knowledge, estimation of the effect of finance on firm productivity endogenously like this has never been used before. We hope that our chapter can help promote a reliable and accurate estimation in this setting to researchers in relevant areas.

To test the hypothesis that less financially constrained firms enjoy higher productivity, we need measures of financial constraint. In the context of China, firm's size and debt-to-asset ratio are found to be very good proxies: larger firms and firms with lower debt ratio tend to be less constrained than their counterparts. Larger firms, with more assets and higher credibility, can more easily obtain loans from banks. Firms with low debt ratio are less likely to get into financial distress; hence, less likely to default on their loans. Small and high-debt-ratio firms, on the other hand, can easily run into trouble and default on their loans, making them not favorable to lenders. To the extend we find significant effects on both these variables in the productivity equation, we conclude that financial constraint does affect productivity, and that we should be very cautious in estimating production function using the traditional ACF approach (or Olley-Pakes (1996)—henceforth, OP—and Levinsohn-Petrin (2003)—henceforth, LP—approach). Results based on the traditional (incorrect) approach are also given for comparison purposes.

4.2 Related Literature

4.2.1 Finance and productivity: Mechanism

Finance can affect firm's productivity through several channels. Brown et al (2009) estimates dynamic R&D (research and development) models for high-tech firms and find significant effects of cash flow and external equity for young, but not mature, firms. The financial coefficients for young firms are large enough that finance supply shifts can explain most of the dramatic 1990s R&D boom, which implies a significant connection between finance, innovation, and growth.

In addtion to R&D, or new invention, Ayyagari et al (2011) has found that access to external financing is associated with greater new-to-firm innovation, defined to include imitation or adoption of new technology from other firms or countries. Though their results are just about positive association, not causality, between finance and new-to-firm innovation, it is believed that finance can affect innovation and firm's production efficiency, which in turn would affect firm's productivity.

Product-quality upgrading could also affect productivity. Simplified and easy-to-assemble designs, for example, should require fewer workers at the same time that they reduce defects. If financial constraint limits firm's ability to upgrade their product, or even lower its quality, we would expect financial constraint to also lower firm's productivity. That tighter credit constraints force firms to produce lower quality goods is confirmed both theoretically and empirically by Fan et al (2015), using higy disaggregated Chinese data.

Finance can also affect other types of investment, for example, fixed capital investment (Fazzari et al, 1988) and inventory investment (Carpenter et al, 1998). Learning-by-investment is a typical argument used to support the positive link between investment and firm's productivity. Together, it can be inferred that finance can also affect productivity by allowing firms to undertake investment more easily.

4.2.2 Cross-country studies

Many studies have explored the links between finance and growth. Theoretically, by employing an endogenous growth model, King and Levine (1993) finds that financial market mobilize savings to finance the most promising productivity-enhancing activities and diversify the risks associated with these activities. As a result, financial system is found to be significant for productivity growth and economic performance. Bencivenga et al (1995) presents a model where developed financial market is needed to support the use of long-gestation capital production technologies. In their model, developed financial system can provide low-cost of funds to firms engaging in innovative activities, in case firms require more funds for their projects before maturity. Theoretical model associated with liquidity risk also shows that liquidity risk of long-term investments can be lessen by more developed financial system, leading to a higher productivity growth (Aghion et al, 2010).

Empirically, by using data on 47 countries, Levine and Zervos (1998) investigate the relationship between measures of stock market development, banking development and long-term economic growth such as productivity (TFP) growth and find that both stock market liquidity and banking development positively and robustly predict the rates of productivity growth. The explanation is that better financial market can increase the ability to trade an economy's productive technologies; thus, ease efficient resource allocation. Similarly, by using data on 63 countries, Beck et al. (2000) find that financial intermediaries exert a large, positive impact on TFP growth, which feeds through to overall GDP growth. Huang and Lin (2009) investigates the non-linear finance-growth nexus and detects overwhelming evidence in support of a positive relationship between financial development and economic growth. They also find that this positive effect is larger for low-income countries than for high-income ones, using data on

71 countries. In constrast, by using a panel of 74 countries, Rioja and Valev (2004) find that finance has a strong positive effect on productivity growth mainly in more developed countries. In less developed countries, the influence of finance on output growth occurs mainly through accumulation of capital. Their finding on less developed countries is inconsistent with Zheng et al. (2009) who find that the main contributor to China's growth is the improvement in productivity rather than the accumulation of factor inputs such as capital.

4.2.3 Firm-level studies

A number of literature has shown that finance and financial constraints can affect firm's real activities such as capital investment (Fazzari et al, 1988), inventory investment (Carpenter et al, 1998), and employment (Nickell and Nicolitsas, 1999). Financial constraint means that firms face a higher cost of external funds than internal funds (cost constraint) and sometimes also face quantity constraint (i.e. cannot obtain external funds such as loans at all). Consequently, these firms have to rely on their internal funds to finance any kind of investments as well as to pay for their factor inputs. Sometimes firms have to forego positive net-present-value investment, due to financial market distortion, refraining firms from attaining higher productivity from learning-by-investment effect.

In addition, if firms want to increase their productivity by undertaking R&D, they will face a lot of difficulties in doing so without a supportive financial market. The intangible nature of R&D (which means lower collateral values of R&D), together with the relatively high uncertainty associated with it, makes bank reluctant to provide loans to the investing firms (Brown et al., 2009).

In short, these papers in general find that measures of financial variables, especially leverage and financial constraints, affect the productivity of firms, which in turns, affect firm's growth, and consequently economic growth as a whole.

One of the most popular approach that studies on the links between finance and productivity employ is an indirect methodology, whereby productivity level of firms is generated first using production-function estimation approaches such as the OP, LP or ACF approach, then this newly generated productivity is regressed on various financial variables deemed important. This common way of estimating financial effect on firm productivity, however, suffer from a serious methodological problem, which is the main addressing objective in our chapter.

4.3 Empirical Implementation

4.3.1 Estimation Methodology

The methology, that incorporates measures of financial constraint directly into the 2nd-stage ACF approach, we use in this chapter is inspired by the work of De Loecker and Warzynski (2012) and De Loecker (2013). Readers can refer to De Loecker (2013) for a rigorous econometric and methodological explanation. For the sake of convenience and more understanding of our chapter, we will explain briefly the mechanism and significance of their technique.

For simplicity, let's consider the following production function (in logs) for firm i at time t generating output (or value-added, y_{it}) from labor (l_{it}) and capital (k_{it}):

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \tag{4.1}$$

where ω_{it} denotes firm productivity, and ϵ_{it} is a standard i.i.d. error term capturing measurement error and unanticipated shocks to production. The point made in this model can be extended directly to more flexible production functions, such as the CES and translog production functions, and gross output instead of value-added production functions. In our empirical specification, we will use gross output (hence, we need to include intermediate input as an addtional regressor) together with translog production function, instead of restricting to the Cobb-Douglas production function, to get results based on more general model.

Production function estimation using proxy estimators, as suggested by Olley and Pakes (1996) (OP), Levinsohn and Petrin (2003) (LP), and Ackerberg, Caves, and Frazer (2006) (ACF) have been widely used in empirical economics. This approach resolves the well-known simultaneity problem and selection biases, and consistently produces parameter estimates associated with the production function together with firm's estimated productivity. This estimated productivity, in particular, can be used to assess the importance of various financial variables on productivity.

Because firm productivity ω_{it} is unobserved, regression estimation in equation (4.1) can be achieved directly. Instead, we have to find proxy for productivity first. OP achieves this by relying on the assumption that the amount of capital (k) chosen by firms depends on their level of employment (l) and productivity (ω). LP and ACF, on the other hand, assume that firm chooses their intermediate input based on their amount of capital (k), level of employment (l) and productivity (ω). In any case, under the assumption that this dependency is monotonic in productivity level (ω), we can proxy ω by these observed factor inputs.

OP, LP and ACF approach mainly rely on an exogenous (first-order) Markov process for productivity, where productivity at time t depends on past productivity, and a productivity shock ξ_{it}:

$$\omega_{it} = g_1(\omega_{it-1}) + \xi_{it} \tag{4.2}$$

This law of motion plays a significant role in providing the identification of the production function coefficients.

The specification given in equation (4.2) nests other traditional approaches used in the literature like OLS, where the productivity process is given by $g_1(\omega_{it-1}) = 0$ and fixed effect, where the productivity process is given by $g_1(\omega_{it-1}) = \omega_i$. The point made in this chapter, therefore, also extends to these methods.

The productivity shock ξ_{it} is uncorrelated with any lagged inputs variables of the firm by assumption. This zero correlation forms the identification conditions for the coefficient of capital in the final stage of the OP/LP procedure, and for both labor and capital coefficients in the final stage of ACF procedure. Using the standard assumption that capital is formed in the previous period, both current and lagged capital would be uncorrelated with productivity shock, and therefore, could be used to identify the capital coefficient. If the objective is to estimate the effects of financial variables or financial constraint on productivity, however, relying on an exogenous productivity process given by (4.2) is problematic; we need to include measure of financial constraint in the productivity process ($g(.)$) first before applying the identification conditions.

More specifically, consider a general model in which financial constraint is allowed to affect future productivity as given by

$$\omega_{it} = g_2(\omega_{it-1}, \mathbf{F}_{it-1}) + \xi_{it}, \tag{4.3}$$

where $\mathbf{F}_{it-1}$ is a vector measuring a firm's financial constraint. For the sake of simplicity, let's assume that $\mathbf{F}_{it-1}$ is a simple variable, f_{it-1}, but the vector $\mathbf{F}_{it-1}$ can be extended to capture other variables as well.

We can identify the parameters of interest by using moment conditions of the productivity shock ξ_{it}, where we have to specify explicitly the productivity process (4.3). Given this endogenous productivity process, we have the following moment conditions:

$$E\left\{\xi_{it}(\beta_l, \beta_k)\begin{pmatrix} l_{it-1} \\ k_{it} \end{pmatrix}\right\} = 0, \tag{4.4}$$

where $\xi_{it}(\beta_l, \beta_k)$ is obtained by nonparametrically regressing $\omega_{it}(\beta_l, \beta_k)$ on $(\omega_{it-1}(\beta_l, \beta_k), f_{it-1})$, and $\omega_{it}(\beta_l, \beta_k) = \widehat{\phi}_{it} - \beta_l l_{it} - \beta_k k_{it}$. We obtain the predicted value, $\widehat{\phi}_{it}$, from a first-stage regression of output (y_{it}) on all the inputs (l_{it}, k_{it}) and the proxy variables including either intermediate inputs or investment, capital, and the firm's financial-constraint status. If we incorrectly assume an exogenous productivity process, the productivity shock (ξ_{it}) contains the productivity effect of financial constraint. Therefore, the coefficient on capital (and maybe labor) will be biased if f_{it-1} is correlated with k_{it} (l_{it-1}). From the above, it is clear that the capital coefficient will be biased if a firm's financial-constraint status is correlated with its (future and current) capital stock, leading to biased estimate of productivity and unreliable results when using this estimated productivity to regress on other variables of interest as observed within the vast literature in this topic.

To verify whether past financial constraint impacts a firm's future productivity, we then rely on $\frac{\partial g_2}{\partial f_{it-1}}$, which depends on the firm's past productivity level (except in our linear process found in Model 1 below).

4.3.2 Empirical specification

Without further ado, let us explicitly lay out our main specification. Our production function we use is of the form:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \omega_{it} + \epsilon_{it}, \tag{4.5}$$

where y_{it}, l_{it}, k_{it} and m_{it} are natural logarithm of firm's gross output, employment, capital and intermediate inputs respectively.

In the first-stage regression of ACF approach, we run by each 2-digit industry an OLS regression:

$$y_{it} = \phi(l_{it}, k_{it}, m_{it}) + \delta.f_{it} + \epsilon_{it}, \tag{4.6}$$

where $\phi(l_{it}, k_{it}, m_{it})$ is a linear combination of $l^s, k^s, m^s, l^s k^p, l^s m^p, k^s m^p$ and lkm, $s = 1, 2, 3, p = \overline{1, s}$, and f_{it} denotes either firm's size (log of deflated total assets) or debt-ratio (total liabilities over total assets). After the first stage, we can compute productivity for any value of $\boldsymbol{\beta}$, where $\boldsymbol{\beta} = (\beta_l, \beta_k, \beta_m, \beta_{ll}, \beta_{kk}, \beta_{mm}, \beta_{lk}, \beta_{lm}, \beta_{km},)$ using $\omega_{it}(\boldsymbol{\beta}) = \phi(l_{it}, k_{it}, m_{it}) + \delta.f_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} - \beta_{ll} l_{it}^2 - \beta_{kk} k_{it}^2 - \beta_{mm} m_{it}^2 - \beta_{lk} l_{it} k_{it} - \beta_{lm} l_{it} m_{it} - \beta_{km} k_{it} m_{it}$.

In the second-stage regression, to allow for different endogenous productivity process, we regress $\omega_{it}(\boldsymbol{\beta})$ on:

(Model 1). ω_{it-1} and f_{it-1}

(Model 2). $\omega_{it-1}, \omega_{it-1}^2, f_{it-1}, f_{it-1}^2$ and $\omega_{it-1} f_{it-1}$

(Model 3). $\omega_{it-1}, \omega_{it-1}^2, \omega_{it-1}^3, f_{it-1}, f_{it-1}^2, f_{it-1}^3, \omega_{it-1} f_{it-1}, \omega_{it-1}^2 f_{it-1}$ and $\omega_{it-1} f_{it-1}^2$.

From this second-stage regression, we recover the innovation to productivity given $\boldsymbol{\beta}, \xi_{it}(\boldsymbol{\beta})$. We can now form moments to obtain our estimates of the production function, where we rely on:

$$E\left\{\xi_{it}(\boldsymbol{\beta})\mathbf{Z}_{it}\right\} = 0, \tag{4.7}$$

where $\mathbf{Z}_{it} = (l_{it-1}, k_{it}, m_{it-1}, l_{it-1}^2, k_{it-1}^2, m_{it-1}^2, l_{it-1} k_{it}, l_{it-1} m_{it-1}, k_{it} m_{it-1})'$ to estimate the production function parameters. We use standard GMM techniques to obtain the estimates of the production function.

The moments above are similar to the ones suggested by ACF and exploit the fact that capital is assumed to be decided a period ahead and therefore should not be correlated with the innovation in productivity. We rely on lagged labor and lagged intermediate input to identify the coefficients on labor and intermediate input since current labor and intermediate input is expected to react to shocks to productivity, and hence $E(l_{it}\xi_{it})$ and $E(m_{it}\xi_{it})$ are expected to be nonzero.

The estimated output elasticities are computed using the estimated coefficients of the production function. The output elasticity for labor (L), for instance, is given by:

$$\widehat{\theta}_{it}^{L} = \widehat{\beta}_l + 2\widehat{\beta}_{ll} l_{it} + \widehat{\beta}_{lk} k_{it} + \widehat{\beta}_{lm} m_{it}, \tag{4.8}$$

Finally, we can look at the effect of past financial constraint on current productivity, our main purpose of this chapter, by calculating $\frac{\partial \omega_{it}}{\partial f_{it-1}}$ from the second-stage regression, for different models as stated above.

4.3.3 Data

The data set used in our study is an annual firm-level unbalanced panel from Chinese Industry Survey (which the National Bureau of Statistics of China has conducted yearly since 1998) for China. Though the original data set covers 1998-2007, we focus only on the period 2003-2007. This is because, for 1998-2007, the production function estimate for several industries for either labor or capital is negative and thus deemed unreliable; any latter study related to this production function will not produce any reliable results either. We try different sample period, keeping in mind the longer the period, the more favorable, and find that only from 2003 onwards that the original estimates of production function are acceptable; hence, we decide on using 2003-2007 in our main model. Again, data set matching and variable construction is similar to the previous chapter.

We focus only on manufacturing firms, defined by the 4-digit industrial code between 1300 (inclusive) and 4400 (firms with industrial code 4300-4400 are considered manufacturing firms, but since there is no information on this industry's output and input price deflator, they cannot be employed in our regressions). The original data comes in separate year; thus, we need to match them into a panel data. Following Brandt et al (2012), we match firms in different years using firm IDs, names, names of legal person representatives, phone number plus city code, and founding year plus geographic code plus industry code plus name of town plus name of main product.[2] After this matching, we end up with an unbalanced panel of firms, with 181,077 firms in 2003 and 312,367 firms in 2007.

[2] This is a more detailed matching procedure than what we use in earlier chapters, as we are able to deal with Chinese names.

We deflate output and intermediate input using 2-digit industrial output and input deflators constructed by Brandt et al (2012). We construct our capital stock series using the following formula:

$$K_{it} = (1 - \delta) K_{i,t-1} + (BK_{it} - BK_{i,t-1}) / PI_{mt} \tag{4.9}$$

where BK_{it} is the book value of capital stock for firm i in year t; PI_{mt} is the price index of investment in fixed assets in year t constructed by Perkins and Rawski (2008); $\delta = 10\%$. The above formula is applied since the birthyear of a firm, where the initial real capital stock K_{i,t_0} is given by:

$$K_{i,t_0} = \frac{BK_{i,t_0}}{PI_{mt}} \tag{4.10}$$

where BK_{i,t_0} is the initial book value of capital stock when firm i was born in year t_0. For firm founded after 1998, this is simply the book value found in the data set for the birthyear. Otherwise, we preject BK_{i,t_0} to be:

$$BK_{i,t_0} = \frac{BK_{i,t_1}}{(1 + g_i)^{t_1 - t_0}} \tag{4.11}$$

where 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 two-digit industry capital stock growth rate of firm i from 1993 to t_1.

We construct real investment I_{it} as

$$I_{it} = (BK_{it} - BK_{i,t-1}) / PI_{mt} \tag{4.12}$$

when the initial data on book value of capital stock in year t and $t - 1$ are available.

Labor is defined as the total number of employment. Size is defined as log of deflated total assets, where as debt-ratio is defined as total liabilities over total assets. Table 4.1 shows descriptive statistics of the variables used in estimation.

4.4 Evaluation of the results

To start off, we provide, for each industry, estimates for production function when productivity is assumed to follow exogenous process and its corresponding number of observations used in the second-stage regression in Table 4.2. All of the coefficients of inputs are positive and of reasonable magnitude as expected, except industry 25. Industry 25 is a petroleum and fuel industry, which is subjected to a lot of inflation (about 250% from 1998 to 2007), making its deflated output relative smaller and does not really rely on labor; as a result, a small negative labor coefficient (-0.017) is not unacceptable.

Next, we present the estimates of the effect of financial constraint, using the approach outlined in Section 4.3. In panel A of Table 4.2 and Table 4.3, we list the average financial-constraint effect for the entire manufacturing sector, where we compare the estimates of the linear model (model 1) with those of the more general model (model 2 and 3). In panel B, we list the estimated effect for each 2-digit industry. There are a few significant findings.

First of all, lower level of financial constraint causes firm's productivity to be higher, on average. Recall that we use two measures of financial constraint: size and debt-ratio. Firms with higher value of size (larger) and/or lower debt-ratio are deemed less financially constrained than their counterparts, all else being equal. To the extent that we find in linear model significantly positive coefficient on size (0.0052), and significantly negative coefficient on debt-ratio (-0.0065), we can infer that financial-constraint plays a significant role in affecting firm's productivity as a whole. The persistence parameter in our linear model is significantly different from one, implying that the AR(1) productivity process is not unacceptable. This negative effect of financial constraint on productivity is confirmed in both model 2 and 3.

Second, the estimates in the more general model (model 2 and 3) indicate that there is an important difference in the estimated effect of financial constraint along the productivity distribution. In column 3, 4, 5 and 6 of panel A in Table 4.2 and 4.3, we list the 25th, 50th, and 75th percentiles of the financial-constraint effect to highlight that the gains from financial constraint differ substantially among the set of firms. Panel B of Table 4.2 and 3 produces the same results for the various industries, and, as expected, we see substantial variation across industries in terms of magnitudes. One persistent picture does emerge: when using size as a proxy for financial constraint, almost all sectors have positive average effects; when using debt-ratio as a proxy for financial constraint, almost all sectors have negative average effects. The same pattern is observed for the median effect. Our result on size is consistent with the finding of Chen and Gualiglia (2013), who document that size affects firm's productivity positively, but differ from them regarding debt-ratio, who find insignificant effect of leverage on productivity. Our result on debt-ratio is more reliable due to the nature of methodological issue: Chen and Gualiglia (2013) generates productivity in the second-stage regression without allowing for any leverage effect, and only includes leverage in the productivity regression afterwards. As discussed in the previous section, if leverage is a significant determinant of future productivity, ignoring its effect when running the second-stage regression would lead to biased and inconsistent estimates of production function and productivity. Our result on leverage is in line with Nucci et al. (2005), who documents a negative relationship between firms' leverage and productivity using data on a panel of Italian firms.

To interpret the magnitude of our results, recall that size is defined as log of total assets and debt-ratio as total liabilities over total assets. An estimated size effect of, for example, 0.0052 in our linear model for the whole sample means that doubling firm's asset would leads to an increase in productivity by 0.52%. An estimated debt effect of, for example, -0.0065 in our linear model for the whole sample means that increasing debt-ratio of a firm by 100% would leads to a decrease in productivity by 0.65%. Though the magnitudes are not large, they are not insignificant. The resulting increase in firm's productivity could have a consequential effect on firm's performance in later periods, as both future productivity and inputs demand would also increase as a result of higher productivity this period.

Results based on the traditional (incorrect) approach are given in Table 4.5 for comparison. Here, in estimating the production function coefficients, productivity is assumed to follow an exogenous AR(1) process. More specifically, we follow almost exactly the procedure described above, except we take the measure of financial constraint f out of the estimation procedure, and we only look at the case of linear AR(1) productivity process. After the coefficients of the production function are obtained, firm's productivity can also be generated, and we regress this newly generated productivity on its first-lag and the first-lag of f (size or debt ratio). Table 4.5 shows that this (incorrect) approach would produce mix effects in the case of size across industries, and smaller (though homogeneous) effects in the case of debt-ratio.

4.4.1 Robustness check

Ownership, especially whether a firm is a state-owned firm (SOE) or not (NONSOE), is always considered one of the most important determinant of a firm's structure in China, and studies that use Chinese firms generally factor it into consideration. SOEs are often subject to a lot of favorable treatment from the government and state-owned banks, making them relatively less constraint, but their performance are also inefficient and therefore, their productivity growth is also low. The effect of financial constraint for SOEs might be significantly different from that of NONSOEs. We address this concern by investigating separately the effect of financial constraint using only SOEs (Table 4.6 and 4.7) and only NONSOEs (Table 4.8 and 4.9). Our finding of the significant effect of financial constraint on firm's productivity remain unchanged across both types of firms.

4.5 Conclusion

In this chapter, we highlight that current methods used to test for the effect of finance or financial constraint on productivity are biased and unreliable. We allow financial constraint to affect a firm's future productivity and show that recent proxy estimators of production functions are a natural framework, as they allow an endogenous productivity process. We show a simple way to correct the bias and apply it to a dataset of Chinese manufacturing firms over the period of 2003-2007, covering 181,077 firms in 2003 and 312,367 firms in 2007, to study the impact of financial constraint on firms' productivity. We have estimated a production function model, using ACF approach by augmenting its second-stage producitivity process with proxy of financial constraint. We found that Chinese firms' productivity is significantly and negatively affected by their degree of financial constraint. Our results were robust to different productivity process and by different proxy of financial constraint. Focusing on a sample of SOEs only and NONSOEs only does not change our finding. Furthermore, using more general productivity processes, we find that the effect of financial constraint on productivity differs substantially across producers, and points to heterogeneity in the impact of financial constraint on firm performance.

These results suggest an important role for financial constraint in productivity growth and warrant further investigation of the underlying mechanisms and their potential policy implications. We reported results for China to show the importance of correcting the bias and of the financial-constraint effect. China is a good case study since its financial system is still underdeveloped despite having high economic growth rate.

One of our drawback is the inclusion of only one variable at a time in the productivity process where several financial variables could be correlated in a consequential way. Future research may attempt to resolve this concern by including more than one financial variable into the productivity process to explore more on the significance of each financial variable. Also, we have used only size and debt-ratio as proxy for financial constraint. Other measures of financial constraint, provided they are good proxies, can be used to provide more understanding of the finance-productivity relationship.

Table 4.1: Descriptive Statistics

	Mean	Standard Deviation
Output	83196.9	730853.3
Labor	231.4	843.9
Capital	21605.7	270150.9
Intermediate input	59240.7	561680.8
Total Asset	69614.4	598764.6
Debt-ratio	0.58	0.55

Note: Output, capital, intermediate input and total asset are all measured in thousands RMB.

Table 4.2: Exogenous Production Function Coefficients

Industrial code	Industry	Labor	Capital	Material	Obs
13	Food processing	0.031	0.024	0.935	44638
14	Food manufacturing	0.071	0.028	0.904	16654
15	Beverage manufacturing	0.045	0.049	0.915	10795
16	Tobacco processing	0.035	0.236	0.837	532
17	Textile industry	0.048	0.023	0.915	70858
18	Garments & other fiber products	0.102	0.031	0.853	36512
19	Leather, furs, down & related products	0.101	0.019	0.870	19062
20	Timber processing, bamboo, cane, palm fiber & straw products	0.099	0.037	0.861	17341
21	Furniture manufacturing	0.055	0.026	0.921	9395
22	Papermaking & paper products	0.045	0.023	0.925	22976
23	Printing industry	0.052	0.070	0.893	14608
24	Cultural, educational & sports goods	0.078	0.021	0.905	10547
25	Petroleum processing & coking	-0.017	0.015	0.946	6951
26	Raw chemical materials & chemical products	0.062	0.028	0.903	56661
27	Medical & pharmaceutical products	0.088	0.062	0.859	15682
28	Chemical fiber	0.013	0.026	0.943	3954
29	Rubber products	0.055	0.027	0.902	9158
30	Plastic products	0.054	0.035	0.905	36836
31	Nonmetal mineral products	0.014	0.019	0.947	62497
32	Smelting & pressing of ferrous metals	0.043	0.017	0.933	18844
33	Smelting & pressing of nonferrous metals	0.033	0.041	0.878	13932
34	Metal products	0.055	0.038	0.898	40970
35	Ordinary machinery	0.061	0.055	0.852	60391
36	Special purpose equipment	0.042	0.037	0.917	30071
37	Transport equipment	0.073	0.039	0.900	35616
39	Electric equipment & machinery	0.064	0.034	0.885	46890
40	Electronic & telecommunications equipment	0.094	0.047	0.846	26449
41	Instruments, meters, cultural & office equipment	0.047	0.040	0.888	10787
42	Other manufacturing	0.087	0.025	0.886	14273

Note: Exogenous productivity process used is: $\omega_{it}=\alpha.\omega_{it-1}+\beta.\omega_{it-1}^2+\gamma.\ \omega_{it-1}^3+\xi_{it}$

Table 4.3: Estimates of Size on Productivity (in percent)

Linear Model (Model 1)		Model 2		Model 3	
Panel A. Whole sample	Estimate (s.e.)	Moment	Estimate	Moment	Estimate
Average effect	0.0052 (0.0002)	25th pct	0.0030	25th pct	0.0030
Persistence	0.6807 (0.0094)	50th pct	0.0044	50th pct	0.0034
		75th pct	0.0050	75th pct	0.0044
Panel B. Industry	Average (s.e.)	Average	Median	Average	Median
13	0.0028 (0.0005)	0.0029	0.0037	0.0035	0.0032
14	0.0051 (0.0007)	0.0036	0.0038	0.0024	0.0022
15	0.0056 (0.0009)	0.0057	0.0063	0.0042	0.0048
16	0.0511 (0.0070)	0.0440	0.0450	0.0414	0.0390
17	0.0025 (0.0007)	0.0026	0.0027	0.0018	0.0013
18	0.0048 (0.0005)	0.0047	0.0049	0.0053	0.0055
19	0.0010 (0.0005)	0.0013	0.0016	0.0005	0.0015
20	-0.0028 (0.0005)	-0.0003	-0.0004	-0.0001	-0.0002
21	-0.0007 (0.0005)	-0.0001	0.0004	0.0006	0.0002
22	0.0024 (0.0005)	0.0020	0.0022	0.0027	0.0023
23	0.0048 (0.0005)	0.0063	0.0066	0.0064	0.0053
24	0.0067 (0.0009)	0.0062	0.0059	0.0052	0.0041
25	0.0254 (0.0044)	0.0179	0.0182	0.0191	0.0188
26	0.0071 (0.0009)	0.0077	0.0079	0.0041	0.0043
27	0.0105 (0.0008)	0.0126	0.0128	0.0104	0.0108
28	0.0013 (0.0006)	-0.0015	-0.0012	-0.0008	-0.0030
29	0.0064 (0.0011)	0.0062	0.0060	0.0046	0.0055
30	0.0018 (0.0003)	0.0019	0.0021	0.0013	0.0019
31	0.0000 (0.0003)	0.0006	0.0007	0.0028	0.0031
32	0.0083 (0.0005)	0.0079	0.0078	0.0084	0.0091
33	0.0084 (0.0007)	0.0034	0.0029	0.0026	0.0010
34	0.0030 (0.0005)	0.0037	0.0038	0.0025	0.0029
35	0.0047 (0.0005)	0.0006	0.0006	0.0016	0.0021
36	0.0176 (0.0018)	0.0083	0.0086	0.0089	0.0095
37	0.0061 (0.0003)	0.0063	0.0063	0.0041	0.0035
39	0.0110 (0.0015)	0.0108	0.0110	0.0071	0.0080
40	0.0115 (0.0014)	0.0040	0.0045	-0.0005	-0.0001
41	0.0279 (0.0060)	0.0248	0.0250	0.0045	0.0052
42	0.0046 (0.0008)	0.0024	0.0025	0.0025	0.0023

Table 4.4: Estimates of Debt-Ratio on Productivity (in percent)

Linear Model (Model 1)		Model 2		Model 3	
Panel A. Whole sample	Estimate (s.e.)	Moment	Estimate	Moment	Estimate
Average effect	-0.0065 (0.0011)	25th pct	-0.0051	25th pct	-0.0041
Persistence	0.6578 (0.0104)	50th pct	-0.0083	50th pct	-0.0052
		75th pct	-0.0098	75th pct	-0.0066
Panel B. Industry	Average (s.e.)	Average	Median	Average	Median
13	-0.0297 (0.0037)	-0.0286	-0.0263	-0.0332	-0.0308
14	-0.0065 (0.0051)	-0.0015	0.0008	-0.0039	-0.0001
15	-0.0204 (0.0059)	-0.0148	-0.0177	-0.0051	-0.0031
16	-0.0691 (0.0263)	-0.0558	-0.0492	-0.0518	-0.0310
17	-0.0112 (0.0045)	-0.0092	-0.0095	-0.0032	-0.0039
18	-0.0012 (0.0010)	-0.0022	-0.0025	-0.0018	-0.0039
19	0.0026 (0.0056)	-0.0039	-0.0023	-0.0036	-0.0025
20	-0.0135 (0.0043)	-0.0094	-0.0094	-0.0111	-0.0316
21	0.0027 (0.0022)	-0.0021	-0.0052	-0.0030	-0.0015
22	-0.0033 (0.0036)	-0.0007	-0.0005	-0.0018	-0.0023
23	-0.0104 (0.0054)	-0.0205	-0.0205	-0.0167	-0.0160
24	-0.0030 (0.0028)	-0.0020	-0.0019	-0.0005	0.0009
25	-0.0195 (0.0061)	-0.0141	-0.0137	-0.0141	-0.0106
26	-0.0267 (0.0045)	-0.0212	-0.0213	-0.0109	-0.0112
27	-0.0104 (0.0018)	-0.0078	-0.0083	-0.0066	-0.0074
28	-0.0253 (0.0102)	-0.0021	-0.0019	-0.0008	-0.0004
29	-0.0286 (0.0058)	-0.0249	-0.0249	-0.0172	-0.0175
30	0.0009 (0.0034)	-0.0044	-0.0044	-0.0031	-0.0046
31	0.0042 (0.0037)	0.0048	0.0043	0.0069	0.0060
32	-0.0236 (0.0020)	-0.0234	-0.0232	-0.0227	-0.0221
33	0.0116 (0.0032)	0.0092	0.0094	0.0076	0.0100
34	-0.0018 (0.0030)	-0.0030	-0.0032	0.0003	-0.0001
35	0.0026 (0.0029)	0.0028	0.0037	0.0035	0.0069
36	-0.0340 (0.0099)	-0.0117	-0.0117	-0.0105	-0.0105
37	-0.0034 (0.0044)	-0.0045	-0.0043	-0.0011	0.0023
39	-0.0085 (0.0040)	-0.0090	-0.0093	-0.0046	-0.0041
40	-0.0054 (0.0045)	-0.0043	-0.0050	-0.0040	-0.0037
41	-0.0178 (0.0157)	-0.0226	-0.0280	-0.0006	-0.0026
42	-0.0071 (0.0073)	-0.0036	-0.0036	-0.0047	-0.0002

Table 4.5: Estimates of Size and Debt-Ratio using Exogenous Productivity (in percent)

	Size		Debt-Ratio	
Panel A. Whole sample	Estimate	(s.e.)	Estimate	(s.e.)
Average effect	-0.0002	(0.0001)	-0.0020	(0.0003)
Persistence	0.6645	(0.0100)	0.6642	(0.0100)
Panel B. Industry	Average	(s.e.)	Average	(s.e.)
13	-0.0016	(0.0003)	-0.0047	(0.0011)
14	0.0000	(0.0003)	0.0024	(0.0032)
15	-0.0004	(0.0003)	-0.0033	(0.0018)
16	0.0029	(0.0037)	-0.0290	(0.0201)
17	-0.0001	(0.0002)	-0.0014	(0.0008)
18	0.0000	(0.0003)	0.0014	(0.0007)
19	-0.0006	(0.0003)	-0.0016	(0.0010)
20	-0.0002	(0.0005)	-0.0043	(0.0021)
21	-0.0007	(0.0005)	0.0028	(0.0017)
22	0.0004	(0.0003)	-0.0023	(0.0010)
23	-0.0003	(0.0004)	0.0014	(0.0021)
24	-0.0004	(0.0008)	0.0021	(0.0023)
25	0.0003	(0.0008)	-0.0040	(0.0038)
26	-0.0008	(0.0002)	-0.0047	(0.0007)
27	0.0002	(0.0003)	-0.0065	(0.0014)
28	-0.0005	(0.0005)	-0.0072	(0.0034)
29	-0.0002	(0.0006)	0.0008	(0.0026)
30	0.0002	(0.0003)	-0.0018	(0.0013)
31	-0.0002	(0.0002)	-0.0010	(0.0010)
32	-0.0003	(0.0003)	-0.0014	(0.0011)
33	0.0007	(0.0004)	0.0000	(0.0018)
34	0.0000	(0.0002)	-0.0009	(0.0012)
35	0.0007	(0.0002)	-0.0093	(0.0008)
36	-0.0006	(0.0004)	-0.0018	(0.0014)
37	0.0000	(0.0002)	-0.0006	(0.0006)
39	0.0001	(0.0003)	-0.0009	(0.0009)
40	-0.0001	(0.0003)	-0.0036	(0.0014)
41	-0.0006	(0.0007)	-0.0069	(0.0034)
42	-0.0001	(0.0005)	-0.0017	(0.0011)

Note: Exogenous productivity process used in ACF approach is: $\omega_{it}=\alpha.\omega_{it-1}+\xi_{it}$.

In estimating the effect of financial constraint, we regress: $\omega_{it}=\alpha'.\omega_{it-1}+\delta.f_{it-1}+\xi'_{it}$

Table 4.6: Estimates of Size on Productivity (in percent)–SOE

Linear Model (Model 1)		Model 2		Model 3	
Panel A. Whole sample	Estimate (s.e.)	Moment	Estimate	Moment	Estimate
Average effect	0.0093 (0.0011)	25th pct	0.0057	25th pct	0.0041
Persistence	0.6299 (0.0372)	50th pct	0.0077	50th pct	0.0062
		75th pct	0.0113	75th pct	0.0081
Panel B. Industry	Average (s.e.)	Average	Median	Average	Median
13	0.0026 (0.0024)	0.0026	0.0030	0.0027	-0.0006
14	0.0103 (0.0043)	0.0074	0.0074	0.0073	0.0081
15	0.0134 (0.0027)	0.0131	0.0130	0.0106	0.0065
16	0.0445 (0.0094)	0.0377	0.0374	0.0345	0.0333
17	0.0076 (0.0028)	0.0053	0.0053	0.0031	0.0016
18	0.0196 (0.0068)	0.0157	0.0142	0.0181	0.0050
19	0.0003 (0.0035)	-0.0060	-0.0053	0.0086	0.0016
20	-0.0053 (0.0032)	-0.0053	-0.0058	-0.0058	-0.0017
21	-0.0094 (0.0082)	0.0014	0.0064	-0.0047	0.0098
22	0.0038 (0.0025)	0.0061	0.0063	0.0034	0.0018
23	0.0021 (0.0013)	0.0040	0.0039	0.0045	0.0039
24	0.0279 (0.0139)	0.0348	0.0462	-0.0172	0.0327
25	0.0299 (0.0076)	0.0156	0.0149	0.0138	0.0149
26	0.0084 (0.0020)	0.0088	0.0090	0.0039	0.0024
27	0.0179 (0.0024)	0.0207	0.0208	0.0215	0.0241
28	0.0061 (0.0044)	0.0001	0.0002	-0.0053	0.0031
29	0.0191 (0.0065)	0.0090	0.0065	0.0103	0.0095
30	0.0047 (0.0062)	0.0039	0.0046	0.0042	-0.0007
31	0.0058 (0.0013)	0.0066	0.0064	0.0094	0.0088
32	0.0061 (0.0030)	0.0075	0.0071	0.0068	0.0079
33	0.0225 (0.0051)	0.0148	0.0152	0.0123	0.0043
34	0.0055 (0.0022)	0.0047	0.0050	0.0034	0.0024
35	0.0078 (0.0018)	0.0039	0.0040	0.0055	0.0059
36	0.0180 (0.0041)	0.0035	0.0034	0.0038	0.0028
37	0.0069 (0.0009)	0.0074	0.0074	0.0049	0.0043
39	0.0041 (0.0042)	0.0034	0.0034	0.0049	0.0080
40	0.0092 (0.0080)	-0.0062	-0.0060	-0.0110	-0.0139
41	0.0118 (0.0066)	0.0018	-0.0002	-0.0010	0.0002
42	0.0278 (0.0208)	-0.0100	-0.0139	-0.0149	0.0052

Table 4.7: Estimates of Debt-Ratio on Productivity (in percent)−SOE

Linear Model (Model 1)		Model 2		Model 3	
Panel A. Whole sample	Estimate (s.e.)	Moment	Estimate	Moment	Estimate
Average effect	-0.0161 (0.0051)	25th pct	-0.0146	25th pct	-0.0057
Persistence	0.6125 (0.0391)	50th pct	-0.0176	50th pct	-0.0132
		75th pct	-0.0237	75th pct	-0.0167
Panel B. Industry	Average (s.e.)	Average	Median	Average	Median
13	-0.0145 (0.0106)	-0.0153	-0.0129	-0.0235	-0.0244
14	0.0252 (0.0262)	0.0115	0.0153	0.0050	0.0193
15	-0.0385 (0.0112)	-0.0314	-0.0315	-0.0039	-0.0196
16	-0.0691 (0.0344)	-0.0452	-0.0344	-0.0390	-0.0081
17	-0.0235 (0.0124)	-0.0135	-0.0142	0.0175	0.0172
18	0.0266 (0.0097)	0.0266	0.0262	0.0255	0.0352
19	-0.0123 (0.0211)	-0.0377	-0.0402	0.0427	0.0127
20	-0.0127 (0.0121)	-0.0021	-0.0045	-0.0009	-0.0019
21	-0.0045 (0.0296)	0.0133	0.0141	0.0273	-0.0160
22	0.0190 (0.0231)	0.0161	0.0137	0.0027	-0.0281
23	-0.0211 (0.0083)	-0.0303	-0.0314	-0.0334	-0.0349
24	-0.1034 (0.0863)	-0.1713	-0.1098	-0.2216	-0.1282
25	-0.0064 (0.0324)	0.0062	0.0028	0.0045	0.0095
26	-0.0336 (0.0090)	-0.0342	-0.0345	-0.0223	-0.0245
27	-0.0220 (0.0075)	-0.0247	-0.0242	-0.0232	-0.0150
28	-0.0449 (0.0279)	0.0028	0.0036	0.0309	0.0364
29	-0.0531 (0.0218)	-0.0112	-0.0107	0.0744	-0.0010
30	-0.0320 (0.0240)	-0.0185	-0.0171	-0.0253	-0.0040
31	-0.0053 (0.0070)	0.0000	0.0003	0.0043	0.0030
32	-0.0280 (0.0100)	-0.0413	-0.0404	-0.0312	-0.0285
33	-0.0213 (0.0124)	0.0006	0.0024	-0.0170	-0.0235
34	-0.0180 (0.0151)	-0.0197	-0.0203	-0.0265	-0.0263
35	0.0055 (0.0163)	-0.0182	-0.0176	-0.0133	-0.0128
36	-0.0377 (0.0307)	-0.0286	-0.0282	-0.0255	-0.0220
37	-0.0042 (0.0113)	-0.0090	-0.0088	-0.0075	-0.0003
39	-0.0169 (0.0134)	-0.0092	-0.0084	-0.0183	-0.0235
40	-0.0224 (0.0115)	-0.0031	-0.0015	-0.0033	0.0161
41	-0.0207 (0.0272)	0.0140	0.0153	0.0078	-0.0076
42	-0.0867 (0.0261)	-0.0505	-0.0584	-0.0741	-0.0334

Table 4.8: Estimates of Size on Productivity (in percent)–NONSOE

Linear Model (Model 1)		Model 2		Model 3	
Panel A. Whole sample	Estimate (s.e.)	Moment	Estimate	Moment	Estimate
Average effect	0.0050 (0.0002)	25th pct	0.0029	25th pct	0.0026
Persistence	0.6833 (0.0097)	50th pct	0.0043	50th pct	0.0033
		75th pct	0.0049	75th pct	0.0046
Panel B. Industry	Average (s.e.)	Average	Median	Average	Median
13	0.0033 (0.0003)	0.0036	0.0048	0.0040	0.0033
14	0.0047 (0.0007)	0.0022	0.0024	0.0012	0.0020
15	0.0047 (0.0009)	0.0046	0.0054	0.0033	0.0038
16	0.0718 (0.0131)	0.0645	0.0626	0.0691	0.0539
17	0.0024 (0.0007)	0.0026	0.0027	0.0015	0.0012
18	0.0046 (0.0005)	0.0042	0.0044	0.0049	0.0055
19	0.0010 (0.0005)	0.0014	0.0016	0.0003	0.0012
20	-0.0025 (0.0005)	0.0004	0.0002	0.0015	-0.0007
21	-0.0006 (0.0004)	-0.0002	0.0000	0.0005	-0.0004
22	0.0024 (0.0005)	0.0015	0.0016	0.0021	0.0022
23	0.0068 (0.0004)	0.0076	0.0083	0.0079	0.0074
24	0.0062 (0.0008)	0.0053	0.0050	0.0044	0.0037
25	0.0249 (0.0046)	0.0176	0.0178	0.0175	0.0169
26	0.0071 (0.0010)	0.0078	0.0080	0.0041	0.0044
27	0.0102 (0.0008)	0.0122	0.0125	0.0099	0.0103
28	0.0015 (0.0006)	-0.0013	-0.0012	-0.0009	-0.0028
29	0.0060 (0.0012)	0.0051	0.0052	0.0037	0.0052
30	0.0018 (0.0002)	0.0018	0.0022	0.0014	0.0021
31	-0.0003 (0.0002)	0.0001	0.0002	0.0023	0.0024
32	0.0085 (0.0005)	0.0086	0.0086	0.0090	0.0092
33	0.0079 (0.0006)	0.0023	0.0015	0.0020	0.0006
34	0.0025 (0.0005)	0.0037	0.0038	0.0023	0.0022
35	0.0049 (0.0005)	0.0008	0.0007	0.0010	0.0019
36	0.0170 (0.0019)	0.0090	0.0094	0.0098	0.0095
37	0.0060 (0.0003)	0.0061	0.0060	0.0041	0.0034
39	0.0118 (0.0016)	0.0118	0.0120	0.0079	0.0080
40	0.0111 (0.0013)	0.0046	0.0052	0.0003	0.0001
41	0.0289 (0.0061)	0.0261	0.0264	0.0048	0.0053
42	0.0036 (0.0006)	0.0020	0.0019	0.0021	0.0015

Table 4.9: Estimates of Debt-Ratio on Productivity (in percent)–NONSOE

Linear Model (Model 1)		Model 2		Model 3	
Panel A. Whole sample	Estimate (s.e.)	Moment	Estimate	Moment	Estimate
Average effect	-0.0049 (0.0010)	25th pct	-0.0031	25th pct	-0.0019
Persistence	0.6605 (0.0107)	50th pct	-0.0066	50th pct	-0.0037
		75th pct	-0.0083	75th pct	-0.0059
Panel B. Industry	Average (s.e.)	Average	Median	Average	Median
13	-0.0320 (0.0014)	-0.0311	-0.0298	-0.0328	-0.0297
14	-0.0107 (0.0034)	-0.0057	-0.0050	-0.0061	-0.0005
15	-0.0139 (0.0065)	-0.0096	-0.0128	-0.0033	-0.0023
16	-0.0611 (0.0383)	-0.0401	-0.0298	-0.0916	-0.0488
17	-0.0098 (0.0047)	-0.0086	-0.0091	-0.0029	-0.0046
18	-0.0019 (0.0010)	-0.0025	-0.0027	-0.0021	-0.0043
19	0.0033 (0.0054)	-0.0039	-0.0017	-0.0027	-0.0018
20	-0.0116 (0.0043)	-0.0082	-0.0088	-0.0125	-0.0289
21	0.0032 (0.0021)	-0.0021	-0.0045	-0.0037	-0.0001
22	-0.0035 (0.0035)	-0.0007	-0.0002	-0.0019	-0.0014
23	-0.0051 (0.0069)	-0.0141	-0.0137	-0.0102	-0.0108
24	-0.0020 (0.0027)	-0.0003	-0.0004	0.0010	0.0020
25	-0.0207 (0.0058)	-0.0147	-0.0145	-0.0070	-0.0211
26	-0.0257 (0.0048)	-0.0188	-0.0188	-0.0099	-0.0100
27	-0.0082 (0.0017)	-0.0062	-0.0071	-0.0050	-0.0070
28	-0.0242 (0.0103)	0.0007	0.0008	-0.0119	0.0050
29	-0.0277 (0.0062)	-0.0202	-0.0202	-0.0164	-0.0157
30	0.0029 (0.0029)	-0.0024	-0.0023	-0.0010	-0.0006
31	0.0054 (0.0039)	0.0071	0.0061	0.0078	0.0060
32	-0.0231 (0.0019)	-0.0228	-0.0227	-0.0223	-0.0214
33	0.0140 (0.0032)	0.0123	0.0145	0.0088	0.0141
34	0.0010 (0.0031)	-0.0021	-0.0026	0.0026	0.0022
35	0.0026 (0.0018)	0.0060	0.0068	0.0051	0.0082
36	-0.0307 (0.0083)	-0.0075	-0.0073	-0.0075	-0.0071
37	-0.0027 (0.0038)	-0.0042	-0.0035	-0.0004	0.0004
39	-0.0085 (0.0042)	-0.0071	-0.0067	-0.0044	-0.0034
40	-0.0042 (0.0047)	-0.0046	-0.0046	-0.0038	-0.0032
41	-0.0164 (0.0157)	-0.0183	-0.0250	0.0028	-0.0024
42	0.0001 (0.0061)	0.0004	0.0005	-0.0030	-0.0008

Chapter 5

Summary

This thesis investigates various topics of financial constraint (and financial friction), ranging from how to determine if a firm is financially constrained, the impact of financial friction on total factor productivity (TFP) of a country, and whether financial constraint affects each firm's productivity. Financial constraint occurs when the cost of raising external funds (equity or debt) is higher than the cost of internal funds (cost constraint) or when there are limits on how much firms can raise external funds (quantity constraint). Under perfect capital market, real investment decision is independent of financial status; in reality, financial friction breaks down this independence and becomes an important determinant of firm investment. As a result, we expect financial friction and financial constraint to play significant roles in governing the performance of each firm and of the country as a whole.

Chapter 1 provides motivation of this thesis, together with general reviews of related literatures on financial constraint.

Chapter 2 investigates empirically the most controversial, yet influential, measure of financial constraint –investment-cash flow sensitivity– using firm-level datasets of U.S. and China. Under a perfect capital market, investment decision is independent of a firm's financial status. Therefore investment will not exhibit any sensitivity to cash flow when investment opportunities are properly controlled for. Imperfections in the capital market, however, can cause a wedge between the cost of internal and external finance. Therefore investment will respond positively to the availability of cash flow if a firm is financially constrained. As a benchmark, this model is applied to a panel of U.S. manufacturing firms from the Compustat, which shows no such sensitivity. In contrast, significant sensitivities are detected on a panel of Chinese manufacturing firms from the Chinese Industry Survey. These results simply indicate that Chinese firms face relatively more financial constraints than firms in U.S. Within U.S, we performs sample-splitting tests for young/old firms, and small/large firms. We found no differences in their cash flow sensitivities. Asymmetric information problems in the U.S seem to be eliminated or largely alleviated by its highly developed financial market. Within China, a hierarchy of sensitivities is found across firms with different age, size, ownership and political connection. A widely expected result is that young (small) Chinese firms are more constrained than old (large) Chinese firms. A more interesting result comes from ownership-splitting regressions. SOEs, COEs, FIEs and OTHERs are found to be unconstrained while DPEs are the most constrained, followed by HMTs. We also contributed additional empirical evidence that political connection helps relieve financial constraints faced by firms, using labor union existence as a proxy. Firms with labor union are, on average, less constrained than firms without labor union. This labor union existence (political connection), together with the risk level, within each firm are conjectured to be the reasons behind different degrees of financial constraint found across firms. Indeed, the data supports this conjecture. Those highly-constrained types of firms are the ones with high level of risks and low level of political connection on average. Finally, our results support the evidence that there is a capital misallocation in China, and that (young, small, DPEs, nonunion) firms cannot take advantage of their high capital productivity by investing more due to them being much financially constrained.

Chapter 3 examines capital misallocation. Capital misallocation exists when firms have different $MRPK$ (marginal revenue product of capital). This difference in MRPK across firms can be due to financial friction or policy distortion. Financial friction in capital misallocation means that although a firm has a high $MRPK$ compared to another firm, this firm cannot increase its capital investment to take advantage of its high $MRPK$ at all, since it needs to raise the necessary fund externally, and since its financial status is viewed by potential investors or lenders as not very good. In a sense, with limited information in hand, investors and lenders justifiably raise the required rate of returns or interest rate for this firm: no ex-ante discrimination or distortion exists along this line. On the other hand, in some cases, even though two firms have identical financial status, they still receive different treatment with regard to rate of return or interest rate required by investors or lenders. We call this kind of distortion "policy distortion". For instance, in the case of China, SOEs (state-owned enterprises) seem to get a better treatment than DPEs (domestic private enterprises) by banks, many of which are state-owned, controlling for their financial status. The main focus of this chapter is to quantify the effect of policy distortion and financial friction in: 1. explaining the difference in $MRPK$ (or user cost of capital) of SOEs, COEs (collectively-owned enterprises), HMTs (Hong Kong, Macau and Taiwan enterprises), FIEs (foreign-invested enterprises), and MIXs (other types of firms) relative to DPEs, and 2. TFP loss due to capital misallocation. Our benchmark results show that policy distortion accounts for about 60%, 60%, 200%, 300% and 130% in lowering user cost of capital respectively for SOEs, COEs, HMTs, FIEs and MIXs relative to DPEs, with the remaining percentage accounted for by financial frictions. We also find that the Chinese manufacturing industry as a whole would enjoy about 70% reduction in capital misallocation when no policy distortion exists. We establish that China is experiencing a TFP loss of about 28.7% per year over 2000-2007 with about 8.6% accounted for by financial frictions and the remaining 20.1% by policy distortions. We also investigate what factors contribute to the existence of policy distortion and financial frictions.

Chapter 4 looks into the effect of financial constraint on firm's productivity. Though there are many studies on the effect of finance on firm's investment, how financial constraint affects firm's productivity, which is a prominent factor for a firm's performance and a country's economic growth, has not received much attention. In addition, those few studies on this linkage have often not been able to produce reliable results due to econometric issues involved. More specifically, they first estimate firm's productivity using production-function-estimation approaches (OP, LP, or ACF) with exogenous productivity process, then use this newly generated productivity to regress on various financial variables to identify financial effects on productivity. However, if finance does affect productivity, not-including financial variables as regressors in the productivity process would lead to biased and inconsistent estimates of production funtion parameters as well as inconsistent estimation of productivity. We attempt to resolve this issue by augmenting various measures of financial constraint directly into the second-stage productivity regression under the ACF approach. We find that Chinese firms' productivity is significantly and negatively affected by their degree of financial constraint. We also find that the effect of financial constraint on productivity differs substantially across producers and industries, and points to heterogeneity in the impact of financial constraint on firm performance.

Though there have been numerous researches attempting at constructing a reliable measure of financial constraints, none of the measure seems to work very well. Studies related to financial constraints usually employ more than one measure/proxy for their robustness check. We hope to see more research on finding a suitable and generally acceptable measure of financial constraint. Research on the effect of financial friction and policy distortion on various economic variable such as investment, productivity, GDP and GDP growth, and its mechanism are also very important and much needed for policy makers to help correct the economy.

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