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Capital Market Distortions in Vietnam: Comparing SOEs and Private Firms

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Abstract

Financial constraints are expected to be severe in Vietnam, especially for private firms, but there is limited evidence for quantifying the gap of financial constraints experienced by SOEs and private firms and the resulting efficiency losses. This paper investigates the size of the capital market distortions using a model of establishment dynamics allowing for different collateral constraints experienced by SOEs and private firms. The parameterized model provides a good match to the targeted data moments but a less satisfactory match to the untargeted data moments calculated from manufacturing panel census (2000-2009). The calibration results show that firms in Vietnam face severe collateral constraints, more so for private firms. Capital distortions across ownership types are an important misallocation channel. The resulting TFP losses are large and robust (ranging from 11.5%-19.1% of GDP). This adds extra evidence to the controversy in the literature about whether financial frictions are able to generate large TFP losses.

Key words: financial constraint, capital market distortion, misallocation, TFP loss

JEL codes: C00, D24, D61, G28, G32

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1. Introduction

Financial markets are important for economic growth and appear to improve the allocation of capital, while the efficiency of capital allocation is negatively correlated with the extent of state ownership in the economy (Wurgler 2000). Ayyagari, Demirgüç-Kunt,and Maksimovic (2008) find robust evidence that obstacles related to finance directly affect firm growth, using firm-level survey data (WBES) for 80 developed and developing countries in 1999 and 2000. Banerjee and Duflo (2005) have summarized the microeconomic evidence pointing to misallocation of capital due to credit constraints and institutional failures, among others, as an important source of productivity differences across countries. But the range of the effect by financial frictions in the literature is wide, reflecting some disagreement regarding the importance of this channel in explaining TFP gaps across countries (Amaral and Quintin 2010, Buera, Kaboski and Shin 2011, Midrigan and Xu 2014). One key explanation in the literature for the wide range of TFP losses from financial constraints is the differences in the persistence of productivity shocks and the ability of establishments to overcome credit market constraints through self-financing (Banerjee and Moll 2010, Buera and Shin 2011, Moll 2014). Financial frictions can reduce aggregate productivity through two channels: 1) preventing potentially productive entrepreneurs from entry (selection effect); and 2) generating misallocation of resources among existing firms.

Despite the fact that the economy has experienced rapid growth in the past three decades, financial frictions may be holding back growth in Vietnam. The financial market is still bank-based and dominated by a few state-owned commercial banks (SOCBs). Market frictions in a transition country like Vietnam are often manifested as SOEs and private firms facing uneven market circumstances, in particular with private firms facing stricter financial constraints than SOEs. The young and small stock market serves almost exclusively for large SOEs (Hakkala and Kokko 2007, Leung 2009).

Nonetheless, there is limited evidence for quantifying the degrees of financial constraints experienced by SOEs and private firms and the corresponding efficiency losses in Vietnam. Ha and Kiyota (2015) apply the theoretical framework from Hsieh and Klenow (2009) to quantify the misallocation loss using enterprise census data (2000-2009) for Vietnam manufacturing firms. They find that the misallocation loss is comparable to those for China and India, and the TFP would increase by 30.7 percent if Vietnam would hypothetically move to “US efficiency”.

Interestingly, they find that the overall misallocation was not reduced in the decade. They argue that this is because the reduction in the output market distortions (entry to WTO) was offset by the increase in capital market distortions (possibly attributable to the global financial crisis). Using the same census data (and also ICS data), Zhou (2015a) investigates whether SOEs and private firms experience unequal distortions in the market for capital (and also for labor and land/buildings). She finds that ceteris paribus, private firms indeed face stricter market distortions for capital (and land/buildings), but the resulting GDP changes from the hypothetical reallocation between SOEs and private firms to neutralize ownership distortions while keeping other distortions unchanged are small and even negative. This is because marginal products increase with firm sizes and SOEs are larger than private firms, counteracting the reallocation gain. The GDP changes increase to 0.6%-11.3% from the hypothetical reallocation if private firms would have the same employment sizes as SOEs from which capital is transferred.

This paper attempts to identify whether and to what extent SOEs and private firms experience unequal financial constraints and further quantify the efficiency losses from financial constraints, using a model of establishment dynamics similar to Midrigan and Xu (2014) but with an extension to allow for different degrees of collateral constraints experienced by SOEs and private firms. With heterogeneous collateral constraints, SOEs and private firms may not be able to borrow the same amount even if they are the same in other aspects. I restrict the analysis to misallocation among existing firms and do not consider distortions on firm entry for the time being.

The model is parameterized to match the salient features of the panel census data (2000-2009) for manufacturing firms in Vietnam. The calibrated model provides a good match to the targeted data moments, which include the standard deviations of output and output growth, the persistence of output, the difference of mean debt-to-capital ratio between SOEs and private firms, and the aggregate debt to output ratio. One untargeted moment considered by Midrigan and Xu, the standard deviation of capital, is also well matched, while the match is less satisfactory to other untargeted data moments such as the standard deviations of labor, labor growth, capital growth, and the persistence of capital and labor. The parameter governing the strength of collateral constraints is much smaller for private firms than for SOEs (0.14 versus 0.42), when using the *firm-level difference* of the average debt-to-capital ratios between SOEs and private firms and the aggregate debt-to-output ratio for identification of the parameters.[2] Thus private firms indeed experience stricter collateral constraints than SOEs. The aggregate TFP loss from misallocation implied by the model is quite large for Vietnam manufacturing (17.4%), contrasting the small misallocation losses for South Korea in Midrigan and Xu (2014).[3]

One caveat with the above analysis is that the gap of collateral constraints between SOEs and private firms may be exaggerated using *raw difference* of the average debt-to-capital ratios for the identification. Private firms may face stricter collateral constraints partially or wholly because they are smaller than SOEs. The difference of the average debt-to-capital ratios between SOEs and private firms is reduced but remains positive and significant when holding firm sizes, sectors, and regions the same. The implied TFP loss is still large using net difference of the average debt-to-capital ratios. The calibration results are robust to modifications in (pre-assigned) parameter values, measurement errors, heterogeneity in borrowing rates, potential sample selection bias, and frictions that hinder firms' responses to productivity shocks (e.g. capital adjustment costs).

This paper contributes to the literature in twofold. First, whether and to what extent capital is misallocated through an ownership channel between SOEs and private firms is a widely debated topic in transition countries with incomplete reforms but the quantitative evidence is at best limited. And, I investigate this issue from a different angle than Dollar and Wei (2007) and Zhou (2015a) in this paper.[4] I find an important ownership channel through which capital is misallocated and private firms face stricter financial frictions than SOEs in Vietnam. This finding is interesting and insightful for policy makers. Second, contrary to the small TFP losses from misallocation for South Korea in Midrigan and Xu (2014), I find large and robust misallocation (TFP) losses for Vietnam ranging from 11.5% to 19.1%.[5] This is because the collateral constraint is more severe and the variation and persistence of productivity shocks are much larger in Vietnam than in South Korea. Hence the paper adds additional evidence to the

[2] The parameter for the collateral constraint ranges between 0 and 1, where zero indicates complete shutdown of debt market and one indicates no collateral constraint in the financial market.
[3] Calibrating the same baseline model from Midrigan and Xu to Vietnam, the implied TFP loss from capital misallocation is 16%, much larger than the 2.5% for South Korea.
[4] The TFP loss here is obtained from removing overall financial frictions. Dollar and Wei (2007) and Zhou (2015a) only calculate GDP changes from removing distortions related to ownership alone but keeping other sources of distortions unchanged.
[5] The misallocation loss for capital market distortion is smaller than the overall efficiency loss of 30.7% (moving to "US" efficiency) from Ha and Kiyota (2015) using the theoretical framework from Hsieh and Klenow (2009).

controversy in the literature about whether financial frictions are able to generate large TFP losses and explain a significant portion of the cross-country productivity gaps.

Related Literature

The paper is related to the vast literature of exploring the role of resource misallocation in explaining TFP gaps across countries. There are different microeconomic measures to approximate misallocation, including the dispersion of marginal products or productivity (Restuccia and Rogerson 2008, Hsieh and Klenow 2009), the within-industry covariance of firm-level productivity and firm size (Bartelsman, Haltiwanger and Scarpetta 2013), and the dispersion of borrowing rates if such data is available (Gilchrist, Sim and Zakrajšek 2013).[6] Among the various imperfections, capital market distortions have been by far the most studied channel of misallocation for both developed and developing countries.

The strand of literature I build on infers the misallocation losses by parameterizing a model with financial constraints to match the salient features of firm-level (producer-level) data. Specifically, Midrigan and Xu (2014) evaluate the efficiency losses from financial constraints with a model of establishment dynamics using producer level data from South Korea. In their model, financial frictions reduce TFP through distorting entry and technology adoption decisions and generating misallocation across existing producers. The parameterization of their model that is consistent with the microeconomic data implies fairly small losses from misallocation (around 2.5%) but potentially sizeable losses from inefficiently low levels of entry and technology adoption.

A few other papers also analyze the impact of collateral constraints. For example, Buera, Kaboski, and Shin (2011) build a 2-sector model with different fixed costs of operation per period, in which financial frictions distort the allocation of capital across heterogeneous production units and their entry/exit decisions. Using census data from US and Mexico and the sectoral-level data from 18 OECD countries, they find that financial frictions account for a large part of the observed cross-country differences in output per worker, aggregate TFP, sector-level relative productivity, and capital to output ratios. Moll (2014) develops a highly tractable general equilibrium model to study the impact of financial frictions on aggregate TFP. He shows that the

[6] Gilchrist, Sim, and Zakrajsek (2013) evaluate misallocation through the dispersion of interest rate spreads on outstanding publicly-traded debt across a subset of U.S. manufacturing firms and find a small TFP loss (3.5%) from misallocation. But the sample for analysis is very selective and may be less financially constrained than firms that are not able to issue public debts.

persistence of productivity shocks determines the size of the steady state TFP losses as well as the speed of transition. More persistent shocks are associated with a small steady state TFP loss but with slow transition, while less persistent shocks are associated with a large TFP loss and fast transition. This is because persistent shocks enable producers to self-finance but it takes time to accumulate assets. Uras (2014) studies the quantitative relevance of the cross-sectional dispersion of corporate financial structure (e.g. pledgeability and liquid asset positions, and marginal rental rate of capital) in explaining the intra-industry allocation efficiency of productive factors, using a heterogeneous-firms model with financial constraints. The model is calibrated to the balance sheet data from seven major industry clusters of the US economy. The counterfactual policy experiments show that weakening the observed balance sheet positions for financially constrained firms leads to a reallocation of production factors from firms with high cost distortions to firms with low cost distortions and causes quantitatively important industry level TFP losses.

On the other hand, Brandt, Tombe, and Zhu (2013) evaluate misallocation of labor and capital *across provinces and sectors* (rather than across firms) for the manufacturing and service sector in China during the period 1985-2007. The overall distortions in factor allocation reduce aggregate non-agricultural TFP by about 20% on average. However, after initially declining, the losses from distortions between state and non-state sectors within provinces increased appreciably since 1997 while losses from between province misallocation remained fairly constant. This reversal can be attributed almost exclusively to increasing misallocation of capital between state and non-state sectors within provinces. They argue that the recent increase in capital market distortions is related to government policies that encourage investments in the state sector at the expense of investments in the more productive non-state sector.[7]

The literature summarized above analyzes distortions in a static framework. The TFP loss in a dynamic framework may well be much larger. For example, Peters (2013) studies the link between misallocation and growth through a tractable endogenous growth model with heterogeneous firms and shows that the dynamic growth effects reducing entry barriers increases growth more than four times than their static counterpart with Indonesian firm-level panel data.

[7] Dollar and Wei (2007) examined the presence of systematic distortions on capital allocation through dispersion of return to capital across ownerships, regions, and sectors. They found SOEs to have a significantly lower return to capital on average than private firms in China for the period 2002-2004.

Asker, Collard-Wexler, and De Loecker (2013) investigate the role of dynamic production inputs and their associated adjustment costs in shaping the dispersion of static measures of capital misallocation within industries across 9 datasets, spanning 40 countries. They find that variation in the volatility of productivity across these industries and economies can explain a large share (80-90%) of the cross-industry (and cross-country) variation in the dispersion of the marginal revenue product of capital.

The structure of the paper is as follows. Section 2 illustrates the theoretical framework for analyzing capital market distortions; section 3 briefly introduces the capital market and presents some descriptive evidence related to possible capital market segregation between SOEs and private firms using enterprise census data (2000-2009) in Vietnam; section 4 presents the calibration procedures and results, as well as various robustness checks; section 5 concludes.

2. The Theoretical Framework for Analyzing Capital Market Distortions

The theoretical framework adopted in this paper builds on the model of establishment dynamics with collateral constraints in Midrigan and Xu (2014). I extend their model by allowing for different degrees of financial frictions experienced by SOEs and private firms, meaning that SOEs and private firms may have different borrowing ceilings even if they are the same in other aspects. Note that in this paper I focus on misallocation among firms in operation only and do not consider distortions on entry.[8]

Why is it important to introduce the heterogeneity of collateral constraints between SOEs and private firms into the model? First, the bank-based financial market in Vietnam is dominated by state-owned commercial banks (SOCBs), which still prefer lending to SOEs. Private firms face much stricter conditions for borrowing from banks (e.g. collaterals, lengthy application procedures, and paper work). The misallocation literature has not dealt with the potential heterogeneity in financial frictions among firms of different ownership types except Dollar and Wei (2007) and Zhou (2015a), where they examined the capital market distortions across firms of different ownership types in China and Vietnam respectively. However, they did not quantify

[8] There are two motivations for ignoring entry. First, the data for firms before entering into formal sector is not available; second, the computational burden is very large for a model with both entry and heterogeneous borrowing constraints for SOEs and private firms. Nevertheless, I leave this for future analysis.

the overall financial frictions and the corresponding TFP losses but rather the relative gaps of factor market distortions between SOEs and private firms and the resulting efficiency gains of neutralizing the gaps found. Second, knowing whether financial frictions differ across ownership types and whether ownership forms an important channel of misallocation can guide policymakers to effectively reduce such frictions and boost economic growth.

Next, I illustrate the model setup in detail. The economy is populated with workers and producers. Both producers and workers aim to maximize their life-time (log) utility given by:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \log(C_t^x), x = m, w \qquad (1)$$

where β is the discount factor and C_t^x is the consumption at period t for x (with $x = m$ for producers and $x = w$ for workers).

2.1 Producers

There are two types of producers, type s (SOEs) and type p (private firms) in the model. They share the same production function technology with decreasing return to scale ($\eta < 1$):

$$Y_t = \exp(z + e_t)^{1-\eta} ({L_t^m}^{\alpha} K_t^{1-\alpha})^{\eta} \qquad (2)$$

where Y_t, L_t^m, K_t denote the output, labor, and capital respectively at period t; z and e_t denote the permanent and transitory productivity components. Following the literature, I assume that the transitory productivity shock e follows AR(1) process.

In each period, producers maximize life-time utility by choosing optimally the amounts of capital, labor, consumption, and investment, subject to a budget constraint and a collateral constraint. Similar to the standard investment literature, I assume the output at period t+1 is produced using capital installed from previous period but the choice of how much to investment at the end of period t is chosen based on the productivity shock e_{t+1} as it is assumed to be observable at the end of period t. This assumption simplifies the analysis by reducing the dimensionality of the state-space. Since the scale of the equity market is still small and unavailable for most firms in Vietnam, the equity issuance is assumed away in the model.[9]

[9] The young and small equity market serves mostly for large SOEs. The average of the equity-to-output ratios in the periods 2000-2009 is around 10%.

The budget constraint for a producer is that consumption and investment spending should be equal to the sum of net profits and new borrowing (without equity issuance):[10]

$$C_t^m + K_{t+1} - (1-\delta)K_t = Y_t - WL_t^m - (1+r)D_t + D_{t+1} \qquad (3)$$

where C_t^m, Y_t, L_t^m, and D_t denote consumption, output, labor, and borrowing respectively at period t for a producer; K_t and K_{t+1} denote capital stock at the beginning of period t and t+1; D_{t+1} is borrowing at period t+1; δ, W, r are capital depreciation rate, wage rate, and interest rate respectively (same for both types of firms).[11] The collateral constraints experienced by producers are that their borrowings cannot exceed a fraction of their capital stocks. The parameters governing the strength of the collateral constraints can be different between SOEs and private firms ($\theta \in [0,1]$) :

$$D_{t+1} \leq \theta_x K_{t+1}, x = s, p \qquad (4)$$

The degree of financial frictions decreases with θ. When $\theta = 1$ the capital market is perfect and there are no collateral constraints, whereas when $\theta = 0$ the capital market is shut down and there is no borrowing at all in the economy. The model allows for different degrees of collateral constraints experienced by SOEs and private firms ($\theta_s \neq \theta_p$). For firms facing more rigid financial frictions, they may have lower debt-to-capital (leverage) ratios and employ more labor to substitute for capital. The limitation of such formulation of the collateral constraints is that all type s (or type p) firms face the same borrowing ceiling. It is likely that firms actually have different borrowing ceilings, for example large firms may have higher debt-to-capital ratios due to their larger sizes.[12]

2.2 Workers

The economy is inhabited by a unit measure of workers. In each period a worker supplies ν_t efficiency units of labor (idiosyncratic efficiency), which evolves according to a finite-state Markov process over time. A worker maximizes lifetime utility (equation (1)) and is subject to

[10] Here investment is equal to $K_{t+1} - (1-\delta)K_t$ while the existing operating income for producers is equal to $Y_t - WL_t - (1+r)D_t$.
[11] It is restrictive to assume that both ownership types face the same depreciation rate, wage rate, and interest rate. I will get back to this later in the robustness checks.
[12] I leave the modeling of the collateral constraint parameters for future analysis.

the budget constraint that consumption and savings should be equal to wage earnings and interests owned:[13]

$$c_t^w + a_{t+1}^w = W\nu_t + (1+r)a_t^w \tag{5}$$

In equation (5), W denotes the wage rate; c_t^w and a_t^w are the consumption and holding of risk-free assets at period t for a worker; and a_{t+1}^w is the holding of risk-free assets at the end of period t. Here I illustrate the worker's problem directly with lower case (rather than upper case) in order to be aligned with the producer problem to be solved, in which all variables will be rescaled by the permanent productivity component ($\exp(z)$) to reduce the dimensionality of the problem (see section 2.3 below).

2.3 The Recursive Formulation of the Model

The net worth of a producer is equal to the difference between capital stock and debt ($A^m = K - D$). To reduce the dimensionality of the problem to be solved, all variables in the model are rescaled by $\exp(z)$. This is possible as profit, output, and the optimal choices of capital and labor are homogeneous of degree one in both net worth A^m and permanent productivity $\exp(z)$.[14] Further denoting the rescaled values with lower case, the Bellman equation for producers along the balanced growth path with constant factor prices W and r becomes:

$$V(a^m, e_i) = \max_{a^{m\prime}, c^m} \log(c^m) + \beta \sum_{j \in n} f_{i,j} V\left(a^{m\prime}, e_j\right) \tag{6}$$

where a^m and c^m are the rescaled net worth and consumption and e is the transitory productivity shock following AR(1) process and is discretized by a Markov process with finite states (n), with $f_{i,j}$ being the transition probability from state i to state j. The budget constraint and the collateral constraint of a producer are reformulated as follows:

$$c^m + a^{m\prime} = \pi(a^m, e) + (1+r)a^m$$

$$k \leq \frac{1}{1-\theta_x} a^m, x = s, p$$

The Euler equation is derived from the optimization of the value function over the optimal choices of consumption and savings:

[13] Since equity issuance is assumed away, workers can only invest in risk-free assets.
[14] See appendix A5 for the details of the rescaling of all variables in the model. This transformation implies that the optimal choice of investment is equivalent to the optimal saving decision.

$$\frac{1}{c(a^m, e_i)} = \beta \sum f_{i,j} \left[1 + r + \frac{\mu_x(a^{m\prime}, e_j)}{1-\theta}\right] \frac{1}{c(a^{m\prime}, e_j)}$$

where $\mu_x(a, e), x = s, p$ denote the multipliers on the borrowing constraints. When the borrowing constraint is (not) binding, the multiplier is positive (zero).

In each period, the choices for both capital and labor are static for given collateral constraints (static decisions). The profit and the first order conditions with respect to labor and capital are written as:

$$\pi(a^m, e) = \max_{k,l^m} \exp(e)^{1-\eta} (l^{m\alpha} k^{1-\alpha})^\eta - Wl^m - (r+\delta)k$$

$$W = \alpha\eta \frac{y(a^m, e)}{l(a^m, e)}$$

$$r + \delta + \mu_x(a^m, e) = (1-\alpha)\eta \frac{y(a^m, e)}{k(a^m, e)}$$

The above first order conditions imply that dispersion in net worth and productivity, in the presence of borrowing constraints, leads to dispersion in the marginal products. The term $r + \mu_x(a^m, e)$ is a proxy for the shadow value of external financing, which is increasing in productivity shock and decreasing in net worth.

For workers, the recursive formulation of the model is similar to producers and is written as:

$$V(a^w, \nu_i) = \max_{a^{w\prime}, c^w} \log(c^w) + \beta \sum_{j \in n^w} p_{i,j} V(a^{w\prime}, \nu_j) \tag{7}$$

where n^w denotes the number of states for the idiosyncratic efficiency shocks to workers and $p_{i,j}$ is the transition probability from state i to state j. The optimization for workers is subject to the budget constraints of $c^w + a^{w\prime} = W\nu + (1+r)a^w$ in each period.[15] Consumption can be substituted away using the budget constraint, leaving saving decision as the only choice variable in the model and simplifying the model to be solved.

2.4 Equilibrium

A *balanced growth equilibrium* is a set of prices W, r, and policy functions for workers ($c^w(a, \nu), a^{w\prime}(a, \nu)$) and producers ($c^m(a, e), a^{m\prime}(a, e)$) that satisfy producer and worker

[15] The optimization problem for workers is simpler as producers face also collateral constraints.

optimizations, the decisions for output, labor, and capital by producers $(y(a,e), l^m(a,e), k(a,e))$, the labor market clearing condition; and the asset market clearing condition. When capital market clears, aggregate savings from workers and producers should be equal to aggregate investment in the economy. With labor market clearing, the aggregate labor demand from producers should be equal to the aggregate efficient labor supply ($L_t = \sum \nu_t$). The capital and labor market clearing conditions respectively can be expressed as below (with both state variables discretized):[16]

$$A^{w\prime} + A^{m\prime} = \sum_{j\in N}\sum_{i\in n} k'(a_j, e_i)$$

$$\sum_{j\in N}\sum_{i\in n} l^m(a_j, e_i) = L = \sum \nu$$

where $A^{w\prime}, A^{m\prime}$ and L denote the aggregate savings from workers and producers ($A^{m\prime} = \sum_{j\in N}\sum_{i\in n} a^{m\prime}(a_j, e_i)$) and aggregate labor demand respectively, and N and n are the total numbers of states for savings a and transitory productivity e. The mean of ν is further normalized to one. Using the aggregate budget constraints for producers and workers, the asset market clearing condition above can be rewritten as:[17]

$$C^m + C^w + I^m = Y$$

which states that aggregate output in the economy is equal to the sum of the aggregate consumptions of producers and workers, and the total investment spending by producers.

2.5 Efficient Allocation

Financial frictions induce misallocation among incumbent firms by not efficiently directing (sufficient) credits to firms with highest marginal products (entry distortion is not considered for now). Let i index producer and M be the set of all producers, and L and K denote the total amounts of labor and capital. Summing up the decision rules for capital and labor across producers gives the following expression for the aggregate output produced:

[16] Note that from here onward the upper cases (C, L, I, Y) are used to denote aggregates in the economy.
[17] Appendix A5 documents the equivalence of the asset market clearing condition with the aggregate budget constraint.

$$Y = \frac{\left(\sum_{i \in M} \exp(e_i)\,(r + \delta + \mu_i)^{-\frac{(1-\alpha)\eta}{1-\eta}}\right)^{1-\alpha\eta}}{\left(\sum_{i \in M} \exp(e_i)\,(r + \delta + \mu_i)^{-\frac{\alpha\eta-1}{1-\eta}}\right)^{(1-\alpha)\eta}} (L^{\alpha} K^{1-\alpha})^{\eta}$$

where financial constraints affect aggregate output through the multiplier μ.

The efficient level of aggregate output is obtained from optimally allocating capital and labor across producers by a social planner to maximize aggregate output, subject to the constraint that the social planner has same amounts of aggregate labor and capital for use as in the original economy. The solution to this problem requires that the marginal products of capital and labor are equalized across producers, and the efficient level of aggregate output is given by:

$$Y^e = \left(\sum_{i \in M} \exp(e_i)\right)^{1-\eta} (L^{\alpha} K^{1-\alpha})^{\eta}$$

Intuitively efficient allocation entails equalization of marginal products and misallocation leads to dispersion in marginal products and hence brings a productivity loss. This is of course restrictive as frictions like capital adjustment costs may also bring dispersion in marginal products. Nonetheless, the TFP loss from misallocation can be calculating by comparing the above efficient aggregate output with aggregate output in the original economy:

$$\begin{aligned} \text{TFPloss} &= \log\left(\frac{Y^e)}{Y}\right) \\ &= \log\left(\sum_{i \in M} \exp(e_i)\right)^{1-\eta} - \log \frac{\left(\sum_{i \in M} \exp(e_i)\,(r + \delta + \mu_i)^{-\frac{(1-\alpha)\eta}{1-\eta}}\right)^{1-\alpha\eta}}{\left(\sum_{i \in M} \exp(e_i)\,(r + \delta + \mu_i)^{-\frac{\alpha\eta-1}{1-\eta}}\right)^{(1-\alpha)\eta}} \end{aligned}$$

With Cobb-Douglas production technology, the shadow cost of capital $r + \delta + \mu$ is proportional to its average product of capital, and the TFP loss is simplified as:

$$\text{TFPloss} = \log\left(\frac{Y^e)}{Y}\right) = \log\left(\sum_{i \in M} \exp(e_i)\right)^{1-\eta} - \log \frac{\left(\sum_{i \in M} \exp(e_i)\left(\frac{y_i}{k_i}\right)^{-\frac{(1-\alpha)\eta}{1-\eta}}\right)^{1-\alpha\eta}}{\left(\sum_{i \in M} \exp(e_i)\left(\frac{y_i}{k_i}\right)^{-\frac{\alpha\eta-1}{1-\eta}}\right)^{(1-\alpha)\eta}}$$

3 Capital Market in Vietnam and the Enterprise Census Data

3.1 Vietnam and the Capital Market

Vietnam is a transition country going through piecemeal reforms since 1986. Economic growth has been fast in the past three decades. The country gradually allowed private and foreign firms to participate in many (but not all) economic activities, marked by the introduction of the Enterprise Law in 2000 and the unified Enterprise Law in 2005. Vietnam became a member of World Trade Organization (WTO) in 2007.

The financial market is still bank-based and dominated by a few state-owned commercial banks (SOCBs). Capital market distortions are perceived to be severe, especially for private firms. SOCBs still prefer lending to SOEs (Hakkala and Kokko 2007, Leung 2009) for three possible reasons: 1) the government-directed lending in favor of SOEs (policy distortion),[18] 2) the information asymmetry between SOCBs and private firms (market imperfection), 3) the cumbersome lending procedure and collateral requirements. Private firms are strictly required to provide collateral for borrowing from banks while most private firms simply lack pledgeable collateral (tangible assets). Even if they manage to obtain loans, private firms often pay higher interest rates than SOEs and the loans are mostly short-term (Hakkala and Kokko 2007). On the other hand, the stock market is still young and small, mostly serving for governments and a few large SOEs.[19] Private firms rely largely on self-financing for investment and also seek capital from the informal financial market.[20] Nguyen and Ramachandran (2006) investigate the determinants of the capital structure for the small and medium firms (SMEs, of which the majority are private firms) in Vietnam and find that firm ownership, firm size, relationship with banks, and networking strongly determine the capital structure of SMEs, reflecting the asymmetric features of the capital market in Vietnam.

[18] For example, Hakkala & Kokko (2007) documents that credits from the Development Assistance Fund (DAF), provincial development funds, the social insurance fund (SIF), and government guaranteed bond issues are less "intrusive", do not require collaterals, and are mostly directed to SOEs.
[19] Vietnam's stock market was established in July 2000.
[20] The informal financial market includes professional money lenders, friends and relatives, and rotating savings and credit associations (ROSCAs, called HUIs in Vietnam).

3.2 Enterprise Census Data (2000-2009)

The data for analysis are the enterprise census data (2000-2009) collected annually by the General Statistics Office (GSO) of Vietnam.[21] It covers all state-owned and foreign invested enterprises, non-state enterprises with at least 10 employees, and 20% of randomly selected non-state enterprises with less than 10 employees, from all sectors in the economy.[22] The census collects detailed information on ownership structure, location, sector, sales, net profits, capital stock, investment, employment, wages, depreciations, taxes, et cetera. But raw materials and energy costs are only available in some years. Value-added is thus calculated as the sum of net profits, labor costs, depreciation, and indirect taxes. Nominal values are deflated by 2-digit industry deflators with 1994 as the base year.

The natural question to ask is whether the panel enterprise census data provide the same picture as the literature regarding the capital market distortions, especially for SOEs and private firms. As a first step, I present some interesting descriptive statistics from the census data. Figure 1 shows that private firms dominate state and foreign firms in numbers in the census.[23] This dominance is reinforced over time. Private and foreign firms have grown more than fourfold in a decade. But private firms are much smaller in terms of employment, capital, and sales relative to SOEs and foreign firms.[24] The capital labor ratio is the highest for foreign firms and smallest for private firms (see table 1).[25] Since private firms are in general small and lack of collaterals, it is possible that they have difficulties in obtaining loans from SOCBs and tend to be more labor intensive as they have to substitute labor for capital in the production.

[21] The data were collected annually between March and May of 2001-2010. See Zhou (2015a) for more details of the census data.

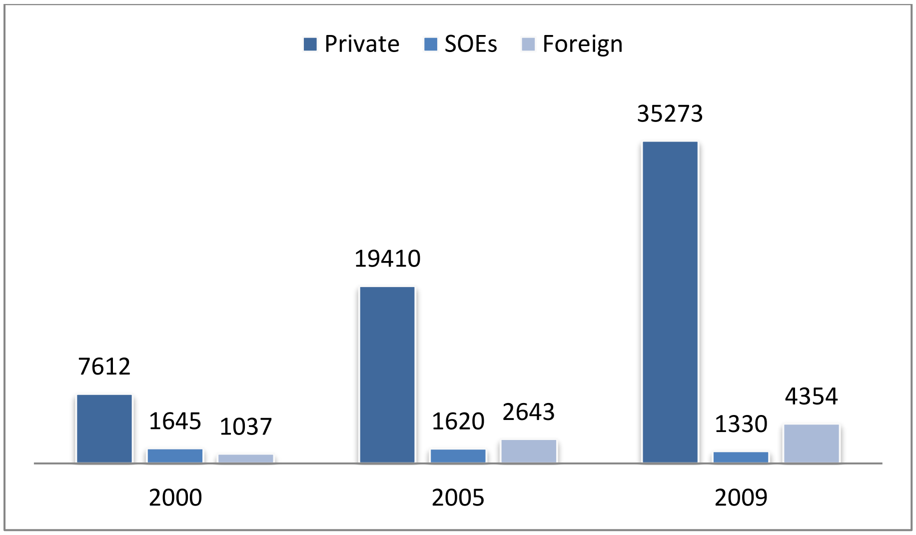
[22] I assign a sampling weight of 5 for the non-state enterprises with less than 10 employees, and a weight of 1 for all other firms. Note that household enterprises (with less than 10 employees and small capital) are excluded in the census but they contribute to Vietnam GDP growth, job creation and poverty reduction significantly (GSO 2012).

[23] Note that figure 1 is produced from the raw data except for removing the observations with duplicates in terms of value added/sales, (end of year) capital, labor, and debt within each year.

[24] To produce tables 1 and 2 and figure 2, I first clean the data: drop observations with duplicates in terms of key variables within each year and observations without time-variation in key variables; trim off the top and bottom 1% of the data for the key variables; and remove the observations with missing values in key variables, where the key variables include output, labor, capital, debts, capital labor ratio, and debt capital ratio. The sectors of tobacco, coke and refined petroleum, office, accounting and computing machinery, and recycling are excluded due to a very small number of observations (including them does not really change tables 1 and 2 and figure 2).

[25] Capital is defined as the end of period fixed assets and long-term investment in the data. Note that the data cleaning for tables 1 and 2 in this paper is a bit different from tables 2 and 3 in Zhou (2015a). Hence the figures are not exactly the same.

Figure 1: Number of firms by Year and Ownership



Source: Vietnam census data 2000-2009. Note: figures are weighted with sampling weights.

Table 1
Firm Sizes and Capital Labor Ratio by Ownership

		Private	SOEs	Foreign
Labor	mean	31	336	249
	p50	8	210	121
Capital	mean	1144	14024	15595
	p50	206	6205	7581
Sales	mean	2677	29804	23787
	p50	332	12942	9386
Capital Labor Ratio	mean	44.0	55.1	112.1
	p50	21.9	28.0	63.6

Note: unit for capital and sales is million VND and the exchange rate of one US dollar to VND ranges from about 14168 in 2000 to 17065 in 2009 according to the World Bank Development Indicators; data are weighted by sampling weights. Source: Vietnam census data (2000-2009).

If private firms face more financial frictions than SOEs, one may expect a smaller fraction of capital financed from loans than for SOEs. Therefore I examine the debt to capital ratio across ownership.[26] Table 2 demonstrates that the average debt to capital ratio has increased from 20% to 42% for private firms and decreased from 61% to 54% for SOEs from 2001 to 2009. But the leverage ratios of SOEs (and foreign firms) remain much larger than those of private firms. The debt-to-capital ratios are quite large in Vietnam compared to the average debt asset ratio of .20

[26] It's defined as the end of year net book values of debt payable over end of year total assets. I skip the statistics for other years to save space as they are similar.

for Compustat firms between 2001 and 2010 (Graham, Leary and Roberts 2014). There are two possible explanations for the large debt-to-capital ratios. First, the end of year net book values of debt payable used for calculation includes not only long term but also short term debts;[27] second, measurement errors on capital in the data will create an upward bias for the average debt-to-capital ratios as it is convex in capital.[28]

Table 2
Debt to Capital Ratio by Ownership and Year (with sampling weights)

year	private		SOEs		foreign	
	mean	median	mean	median	mean	median
2001	0.20	0.06	0.61	0.63	0.41	0.38
2005	0.27	0.23	0.57	0.60	0.47	0.47
2009	0.42	0.44	0.54	0.56	0.49	0.48
AVG	0.27	0.20	0.59	0.61	0.46	0.45

Note: the top/bottom 1% of debt asset ratio are trimmed off per annum; source: same as table 1

The financing structure for different ownership types can also reflect capital market distortions to some extent. Nguyen and Ramachandran (2006) have already shown that firm ownership and firm size (and relationship with banks and networking) largely determine the capital structure of SMEs, among which the majority are private firms. For example, private firms may rely heavily on self-financing and borrow less from banks while SOEs may finance a large part of their investments from bank credits. Therefore I investigate whether the financing structure is different between SOEs and private firms below.

Firms can finance investment from own capital, loans, state budget, and other sources in the census data. The sources of financing for firms for 2000 and 2009, and for different ownership types and sizes are presented in figure 2. Panel A of figure 2 shows that 84% of private and foreign firms finance investment from own capital against 68% for SOEs. 42% of the SOEs finance investment from loans compared to only 27% for private firms and 21% for foreign firms. Another 16% of SOEs also finance investment from state budget, which is not available for

[27] The composition of long term and short term debts may be different across ownership types. SOEs may have larger fractions of long term debts than private firms. SMEs in Vietnam employ mostly short-term liabilities to finance their operations (Nguyen and Ramachandran 2006).

[28] Let $\frac{D}{K}$ denotes the debt to asset ratio and ε the measurement error on capital. The ratio is convex in assets and hence $E\left(\frac{D}{K}\right) < E\left(\frac{D}{K+\varepsilon}\right)$. If the measurement errors do not vary systematically across ownership types, the order of magnitude can be maintained.

private and foreign firms. But this financing structure may be related to firm sizes. Hence I also look at the financing structure for firms with different sizes. The percentage of small firms financing from loans is only 23% versus 38% for large firms. 86% of small firms report self-financing for investment against only 77% for large firms.

Panel B of figure 2 shows the contribution to aggregate investment of each finance source in 2000 and 2009 and for each ownership type and size group. Own capital and loans are the two major sources of financing for aggregate investment in Vietnam. But the share of loans in aggregate investment has fallen from 41% in 2000 to 38% in 2009, meanwhile the share of own capital in aggregate investment has increased from 48% to 52%. In particular, 47% of the aggregate investment for SOEs is financed from loans compared to only 31% for private firms and 25% for foreign firms. Accordingly, the share of own capital in aggregate investment is much lower for SOEs than private and foreign firms (33% versus 57% and 61%). Other source of financing takes up 12%-14% of aggregate investment in 2009 for all ownership types. Last but not least, state budget also accounts for 8% of the aggregate investment for SOEs but almost zero for private and foreign firms.

The message conveyed in figure 2 is that SOEs and private firms have different financing structures as expected. This may have to do with different degrees of financial frictions across ownership types. When looking at the financing structures across firm sizes, as large as 70% (18%) of the aggregate investment is from self-financing (loans) for small firms, compared to 49% (36%) for large firms. Since ownership is positively correlated with firm sizes, the different financing structures between SOEs and private firms found here may be partly caused by the fact that SOEs are overall much larger than private firms. When performing a regression of debt-to-capital ratios on ownership dummies, controlling for firm size, sector, and region, the coefficient for SOEs dummy is indeed reduced but remains significantly different from zero.[29]

In sum, the descriptive statistics from the panel census data above show that SOEs are larger, more capital intensive, and have higher leverage ratios on average, and finance more from loans and less from own capital, compared to private firms. These statistics are in line with the hypothesis that private firms face more financial frictions than SOEs in Vietnam, although it is confounded to some extent by firm size as private firms are much smaller than SOEs in the data.

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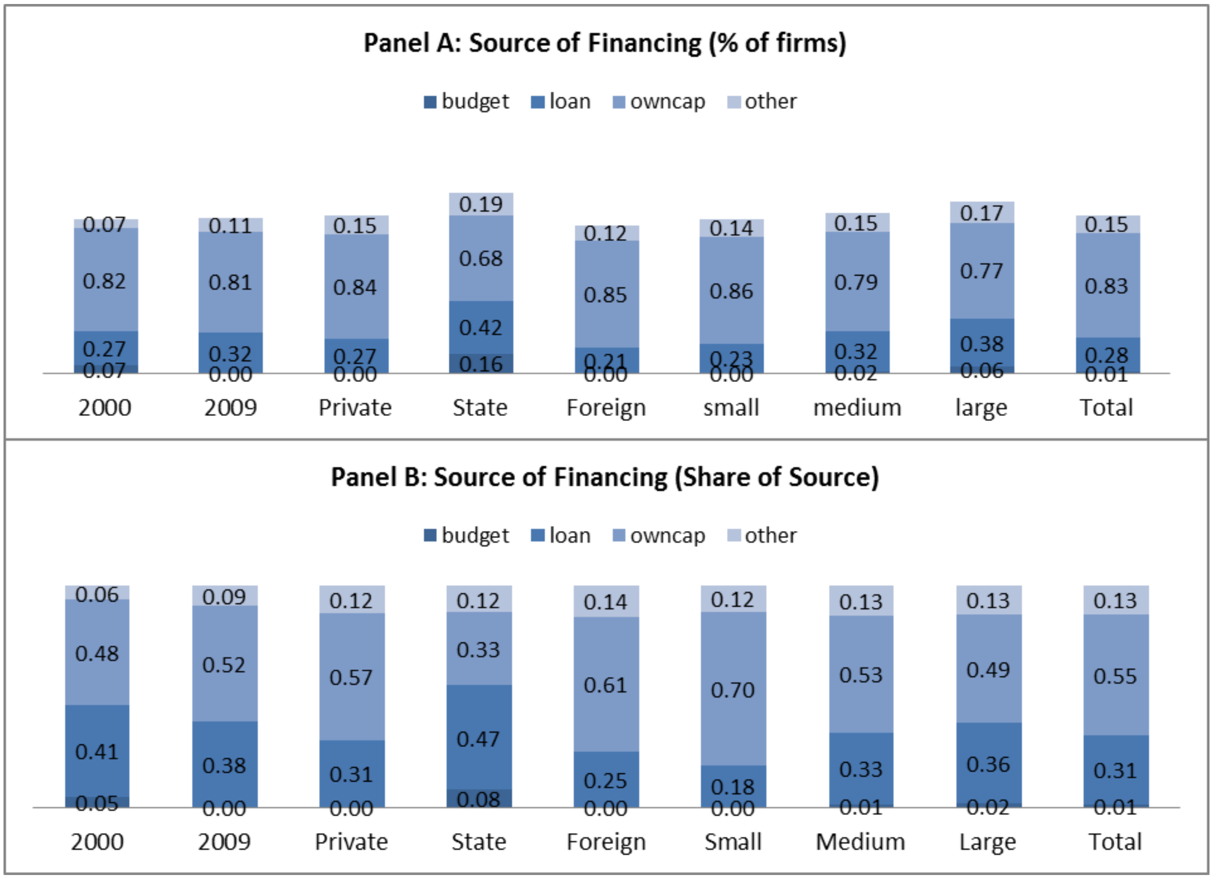
[29] I return to this later in the calibration section. The details of the regression are documented in appendix A6.

Figure 2: Source of Financing, by Year, Ownership, and Size



Source: Vietnam Census 2000-2009. Note: figures are weighted with sampling weights.

4 Quantitative Analysis

This section presents the details of the calibration procedures, calibration results, and some robustness checks, using panel census data (2000-2009) for manufacturing firms in Vietnam.

4.1 Model Identification and Calibration

The purpose of calibration is to find the underlying structural parameters that ensure the microeconomic implications of the model match with the salient features of the firm-level data, namely the panel census data (2000-2009). The details of the data cleaning and calculation of the data moments for calibration are documented in appendix A1.

Since the model focuses on existing firms (without entry and exit), ideally one should calculate the data moments for calibration from a balanced panel. But the balanced panel census data with

10 years covers less than 5% of the original data and hence the selection bias is likely to be severe. To reduce the selection bias, I calculate the data moments to be used in calibration from 6-year moving windows from the panel census data.[30] The 6-year moving windows from the panel comprise up to 30% of the cleaned data. Specifically, I calculate data moments from each of the five moving windows (2000-2005, 2001-2006, 2002-2007, 2003-2008, and 2004-2009) and then take the averages of the data moments calculated from the five moving windows for calibration.

Measurement errors are likely to be large in the census data, particularly for output (value-added) and capital. Both standard deviation and persistence are sensitive to measurement errors (e.g. outliers). Therefore to reduce the impact of outliers, the top and bottom 1% of the data for the key variables are trimmed off before producing the data moments for calibration.[31]

Parameterization

There are two types of parameters in the model. The first type includes the preference and technology parameters that are difficult to calibrate. I assign the same values to these parameters as Midrigan and Xu (2014). Therefore, the capital depreciation rate (δ), the returns to scale (η), and the elasticity of labor in production (α) are set to be 0.06, 0.85, and 2/3 respectively. The efficiency of a worker is assumed to follow a two-state Markov process with $\nu_t \in \{0,1\}$. The probabilities of staying in the zero state and unit states are assumed to be .5 and .79 respectively, same as Midrigan and Xu (2014).[32]

The rest of the parameters are calibrated, including the standard deviation and persistence of transitory productivity shocks (σ, ρ), the standard deviation of permanent productivity (σ_z), and the parameters governing the strength of collateral constraints for SOEs and private firms

[30] At least 6 years of data are required as the autocorrelation of output with horizon 1, 3, and 5 are used for identification of autocorrelation coefficient. Therefore only firms appearing at least 6 years continuously in the panel are kept. Selection bias may remain a concern and see appendix A2 for more on this. Details of data cleaning can be found in appendix A1.

[31] A few examples of the measurement errors include duplicates in terms of key variables within each year, inconsistency of panel identifiers over time, and negative or missing values for key variables used for calibration (e.g. value added, capital, labor, et cetera). Value added in the census is calculated as the sum of net profits, wages, depreciations, and indirect taxes while capital is the end of year book value of total (fixed) assets. Compared to the data cleaning for tables 1 and 2, the data cleaning for model calibration further remove firms with less than 6 years of data as well as firms with gaps.

[32] The World Bank indicator of the labor force participation rate for Vietnam is around 77%, somewhat larger than the 70% for South Korea.

(θ_s, θ_p). The variation of log output and output growth and the autocorrelations of log output (of horizon 1, 3, and 5) can be used to pin down the standard deviation and persistence of productivity shocks.

For the identification of the collateral constraint parameters for SOEs and private firms (θ_s, θ_p), at least two conditions are required. The strength of the collateral constraints determines the size of borrowing. In equilibrium aggregate borrowing should not exceed aggregate credit supply. Therefore the aggregate debt-to-output ratio can be used for the identification of the parameters for collateral constraints. The data point for the aggregate debt-to-output ratio is the World Bank indicator of domestic credit to private sector as a percentage of GDP for Vietnam, which has steadily increased from 32.7% in 2000 to 103.3% in 2009 with a 10-year average of 67.7%.[33] With a binding borrowing constraint, the debt-to-capital ratio of a firm should be equal to the parameter governing the degree of collateral constraints, otherwise it is smaller. On average the debt-to-capital ratios should be smaller than θ_s for SOEs and θ_p for private firms respectively (they are equal only if all firms face binding collateral constraints, which hardly holds). But the difference of the *average* debt-to-capital ratios between SOEs and private firms may be approximately equal to $\theta_s - \theta_p$. Hence the difference of the average debt-to-capital ratio between SOEs and private firms can be used as another condition for identifying the parameters governing the collateral constraints for SOEs and private firms.

The second identification condition above can be explained further with equations below. If $\frac{D}{K}$ denotes the debt-to-capital ratio and N_x denotes the number of firms from ownership type x, the following equation holds:

$$\left(\frac{D}{K}\right)_{ix} = \theta_x - \varepsilon_{ix}, \varepsilon_{ix} > 0\,, x = s, p$$

where ε_{ix} measures the deviation from θ_x (inefficiency term) for firm i. The debt-to-capital ratio is equal to θ_x only if the borrowing constraint is binding. Taking the averages of debt-to-capital ratios for both ownership types:

[33] The data are for the whole economy and the data for manufacturing sector are not available.

$$\overline{\left(\frac{D}{K}\right)_x} = \left(\frac{1}{N_x}\sum_{i=1}^{N_x}\left(\frac{D}{K}\right)_{ix}\right) = \theta_x - \overline{\varepsilon_x} < \theta_x$$

The difference of the average debt-to-capital ratios between SOEs and private firms is written as:

$$\Delta\left(\frac{D}{K}\right)_{sp} = \overline{\left(\frac{D}{K}\right)_s} - \overline{\left(\frac{D}{K}\right)_p} = \theta_s - \theta_p + \overline{\varepsilon_p} - \overline{\varepsilon_s}$$

The difference of average debt-to-capital ratios is approximately equal to $\theta_s - \theta_p$ if the averages of the inefficiency terms for SOEs and private firms are similar to each other ($\overline{\varepsilon_p} - \overline{\varepsilon_s} = 0$). However, if there are a larger fraction of private firms facing binding constraints than SOEs, this is equivalent to $\overline{\varepsilon_p} < \overline{\varepsilon_s}$. As a result, the average debt-to-capital ratio for SOEs should be much smaller than θ_s while the average debt-to-capital ratio for private firms should be close to θ_p. In such case, the difference of average debt-to-capital ratios between SOEs and private firms may be smaller than $\theta_s - \theta_p$. On the other hand, the higher debt-to-capital ratios for SOEs than those for private firms are caused partially by the fact that they are larger than private firms in the data.[34] One could model the parameters for collateral constraints as a function of firm size to isolate the influence of firm sizes on leverage ratios. But in this case the identification of the parameters would be different and more difficult. I leave this for future analysis.

Next, I briefly illustrate how to solve for the model of establishment dynamics described above. Similar to Midrigan and Xu (2014), the value function is approximated with spline approximation (with two state variables); the optimal choices of capital and labor for producers are solved by Newton method before solving the dynamics (namely the decision rules for capital and labor are static for given collateral constraints); and the dynamic program is solved with projection methods (to obtain the optimal savings decision rule).[35] The model is solved separately for workers, SOEs, and private firms. The procedures for solving the model are the same for both ownership types and the only difference is that they face different degrees of collateral constraints (hence with different decision rules). The aggregate demand for capital

[34] In the theoretical model, the only difference between SOEs and private firms is the ownership, whereas in the data SOEs and private firms are different in many other aspects. For example in the data SOEs are much larger than most private firms in employment sizes, capital, and sales.

[35] The details of projection methods and codes can be found in textbook "Applied Computational Economics and Finance". The programming procedures for the paper are documented in appendix A4.

(labor) is the sum of the aggregate demand for capital (labor) from both SOEs and private firms. In equilibrium, aggregate demand for capital should be equal to the sum of the aggregate savings from workers, SOEs, and private firms, while aggregate labor demand should be equal to aggregate labor supply. Simulation is performed separately for SOEs and private firms using the decision rules obtained above. The simulated data for both ownership types are further pooled together to produce key moments, which are further compared with the targeted data moments.

4.2 Calibration Results

A. Model with Homogenous Collateral Constraints

I begin with replicating the baseline model without entry from Midrigan and Xu (2014) where all firms face the same degree of collateral constraints to see whether the model can produce microeconomic implications close to the salinet features of the census data from Vietnam. Panel A of table 3 presents the data moments for calibration calculated from the 6-year moving windows of the panel census. Two sets of data moments are calculated with one using fixed capital and the other using total capital. But most of the targeted data moments are similar regardless of which measure to use.[36] The data and model-implied moments for South Korea (label 'South Korea') from Midrigan and Xu (2014) are included in table 3 as well for comparison. The standard deviations and persistence for output, labor, and capital are larger in Vietnam but the standard deviations for the growth of output, labor, and capital (with fixed capital) are similar compared to South Korea. The debt-to-output ratio for Vietnam is approximately half of that for South Korea (.68 versus 1.20).

The baseline model provides a good match to the targeted data moments and also to the untargeted standard deviation of capital as shown in table 3. But the match to other data moments not explicitly targeted is less satisfactory. Specifically, the standard deviation of capital growth is smaller while the persistence of capital is much higher in the model than in the data.[37] Moreover, the model implied standard deviations for both labor and labor growth are larger than in the data.

[36] Midirigan and Xu (2014) use fixed capital for calibration. I include data moments calculated from total capital in order to compare with the calibration results for the extended model later on, which use total capital for calibration.
[37] When increasing the depreciation rate from .06 to .08, the model fit for the targeted data moments remain good and the gap for the variance of capital growth between the model and data is smaller (results are available upon request).

The corresponding calibrated parameters for the baseline model are presented in table 4. Again the parameters for South Korea are included for comparison (label 'South Korea'). The table shows that the calibrated parameters are quite similar whether using fixed capital or total capital. The calibrated misallocation loss is almost 16% for Vietnam, much larger than the 2.5% for South Korea. This is because financial frictions are much more severe (0.26 versus 0.57), the within variation of transitory productivity shocks is much larger (1.62 versus 0.83), and finally the productivity shocks are also more persistent (0.54 versus 0.30) in Vietnam than in South Korea. The cross-sectional variation of the permanent productivity is also much larger in Vietnam than South Korea (2.94 versus 1.43). Hence the model is able to generate a large misallocation loss when calibrated to match the key data moments for the census data in Vietnam.

Table 3
Baseline Model: Match of Data and Model Moments

	Fixed Capital Vietnam		Total Capital Vietnam		Fixed Capital South Korea	
	Panel A: Targeted Data Moments					
	Data	Model	Data	Model	Data	Model
SD output	1.94	1.94	1.92	1.92	1.31	1.31
SD output growth	0.63	0.62	0.63	0.61	0.59	0.58
Autocorrelation lag 1 output	0.95	0.95	0.95	0.95	0.90	0.90
Autocorrelation lag 3 output	0.91	0.90	0.91	0.90	0.87	0.86
Autocorrelation lag 5 output	0.88	0.88	0.88	0.88	0.85	0.86
Debt to output ratio	0.68	0.67	0.68	0.67	1.20	1.20
	Panel B: Other Data Moments Not Targeted					
	Data	Model	Data	Model	Data	Model
SD capital	1.96	1.87	1.87	1.85	1.44	1.27
SD capital growth	0.57	0.13	0.34	0.14	0.57	0.44
SD labor	1.54	1.94	1.53	1.92	1.21	1.31
SD labor growth	0.45	0.62	0.37	0.61	0.49	0.58
Autocorrelation lag 1 capital	0.96	1.00	0.98	1.00	0.92	0.94
Autocorrelation lag 5 capital	0.86	0.97	0.93	0.97	0.86	0.92
Autocorrelation lag 1 labor	0.96	0.95	0.97	0.95	0.92	0.90
Autocorrelation lag 5 labor	0.88	0.88	0.92	0.88	0.86	0.86

Note: in the baseline model all firms face the same borrowing ceiling.

Table 4
Parameters Calibrated for Baseline Model

	Fixed Capital Vietnam baseline	Total Capital Vietnam baseline	Fixed Capital South Korea baseline
$\boldsymbol{\theta}$	0.26	0.26	0.57
$\boldsymbol{\rho}$	0.54	0.55	0.30
$\boldsymbol{\sigma}$	1.62	1.61	0.83
$\boldsymbol{\sigma_z}$	2.94	2.87	1.43
Misallocation loss	16.0%	16.0%	2.5%

B. Model with Heterogeneous Collateral Constraints for SOEs and Private Firms

Next I proceed to calibrate the extended model where SOEs and private firms face different degrees of financial frictions. Since the analysis focuses on SOEs and private firms, I exclude foreign firms from the data for calibration, although the calibration results are similar whether or not foreign firms are included.[38] As mentioned before, the aggregate debt-to-output ratio and the difference of the average debt-to-capital ratios are used to identify the degrees of collateral constraints. The debt-to-capital ratio in the model should be between 0 and 1. But a large fraction of the debt-to-capital ratios calculated in the data are well above 1 when capital is measured by the end of year fixed assets (including long-term investments). Once I replace fixed assets with total assets, the debt-to-capital ratios for the majority of the observations in the data are between 0 and 1, although the ratios remain large. Measurement errors in the capital data and the inclusion of both long term and short term debts from all sources lead to upward bias in the debt-to-capital ratios. Nevertheless, for the calibration of the extended model, I calculate the difference of the average debt-to-capital ratios between SOEs and private firms where capital is measured as total assets.

The parameterized extended model also provides a good match to the targeted data moments and the untargeted standard deviation of capital, but the match to the other untargeted data moments is less than perfect (see table 5, columns (1)-(2)). Specifically, the model implied that the standard deviation of capital growth is much smaller than in the data while the standard deviations of labor and labor growth implied by the model are much larger than in the data. Meanwhile, the persistence is stronger for capital but somewhat weaker for labor in the model than in the data.

Table 6 lists the calibrated parameter values (row 1) for the extended model with heterogeneous borrowing constraints. The calibration results confirm that financial constraints are severe in Vietnam, and private firms experience stricter financial constraints as the parameter of collateral constraints is much smaller for private firms than SOEs (.14 versus .42). The misallocation loss has increased slightly compared to the baseline model with homogenous financial constraints (17.4% versus 16.0%). There are two explanations for the increase in misallocation loss relative

[38] The calculated standard deviations of output and output growth as well as the autocorrelations of output of horizon 1, 3, and 5 are similar with or without foreign firms.

to the baseline model. First, rather than experiencing the same degree of collateral constraints, private firms now experience much stricter collateral constraints than SOEs. Second, the dominance of private firms over SOEs in numbers in the model and in the census data (86% private firms against 14% SOEs) exacerbates the misallocation loss.

4.3 Robustness Checks

In this section I explore some variations of the assumptions in the model to check if the calibration results presented above are robust, including controlling for possible confounding effects by firm size, variation in the pre-assigned parameter values, measurement errors (outliers and multiplicative measurement errors), and frictions that hinder a firm's response to productivity shocks such as the capital adjustment costs.

Firm Size

The first robustness check considered here is the potential confounding effects by firm size. In the model, SOEs and private firms are the same except that they may face different borrowing constraints, whereas in the data SOEs and private firms differ in many aspects. For instance, SOEs are larger than private firms in terms of capital, labor, and sales, and also have higher debt-to-capital ratios. The higher leverage ratios may have to do with the larger scales of SOEs (and can borrow more than small firms). Therefore using the raw difference of the average debt-to-capital ratios between SOEs and private firms for identifying the parameters of collateral constraints may exaggerate the gap of the collateral constraints experienced by SOEs and private firms. When doing a regression of the debt-to-capital ratios on dummies for ownership, size, sector, and region, the coefficient for SOEs dummy is only 0.06 (but remains significantly different from zero), which is much smaller than the raw difference of the average debt-to-capital ratios between SOEs and private firms (0.27). Meanwhile the coefficients for medium and large firms are 0.21 and 0.28 (and significant) respectively. The coefficients for sector and region dummies vary largely but the overall contribution to the difference is small. The regression results confirm that the large difference of the average debt-to-capital ratios between SOEs and private firms is largely related to the differences in firm size.[39] Therefore I calibrate the extended baseline model again using the net difference rather than the raw difference of average debt-to-

[39] The regression results are documented in appendix A6.

capital ratios between SOEs and private firms (0.06) to isolate the confounding effects from firm size.

The match of the data moments remains similar as before (see table 5 columns (3)), namely the match to the targeted data moments is good while the match to untargeted data moments is still less than perfect. Table 6 (row 2) presents the calibrated parameter values. As expected, the difference $\theta_s - \theta_p$ becomes smaller. But it remains true that private firms face more collateral constraints than SOEs and the calibrated misallocation loss is reduced but remains as large as 16.4%.

The net difference of the average debt-to-capital ratios (0.06) can be treated as the lower bound of the financial constraint gap between SOEs and private firms. The upper bound of the gap is not clear, depending on the relative strength of two contrasting forces. The first is that there may be a larger fraction of private firms with binding collateral constraints than SOEs (as the former experience stricter financial constraints), and in such case the financial constraint gap $\theta_s - \theta_p$ should be larger than the raw difference of average debt-to-capital ratios (if meanwhile SOEs and private firms would be the same in all other aspects, $\theta_s - \theta_p > 0.27$). But on the other hand, SOEs are larger than private firms in general, making the actual financial constraint gap smaller than the difference of the average debt-to-capital ratios between SOEs and private firms ($\theta_s - \theta_p < 0.27$). It is unclear which effect dominates and hence 0.27 can be roughly treated as the upper bound of the financial constraint gap as SOEs are much larger than private firms. The actual financial constraint gap $\theta_s - \theta_p$ is most likely to be between 0.06 and 0.27. Therefore I set the difference of the average debt-to-capital ratios to 0.12 and recalibrate the model again (see column (4) of table 5 and row 3 of table 6). The calibration results are again similar as before. The misallocation loss is 16.5%, slightly higher than the TFP loss of 16.4% from using the net difference of the average debt-to-capital ratios. This variation also shows that misallocation losses actually increase with the gap of the financial constraints between SOEs and private firms for a given level of financial development in the economy.[40] Hence it corroborates the hypothesis that ownership distortion between private firms and SOEs is an important misallocation channel.

[40] The level of financial development for the economy is pinned down by the aggregate debt-to-output ratio.

Depreciation Rate

*Next***,** I explore whether the match of the model to the untargeted data moments can be improved by varying the values of some pre-assigned parameters (see columns (5)-(7) of table 5). A low depreciation rate may result in high persistence and small within-firm variation in capital. Therefore I increase the depreciation rate from 0.06 to 0.08 and 0.10 respectively and recalibrate the model.[41] The match to the targeted data moments by the extended model remains reasonably well when the depreciation rate is increased to 0.08 and 0.10. The model implied standard deviation for capital growth has increased somewhat and the persistence of capital has decreased slightly, especially when the depreciation rate increases to 0.10. The match to the standard deviation of capital growth and persistence of capital has improved relative to benchmark case with the depreciation rate equal to 0.06. But the model implied variances of labor and labor growth are insensitive to changes in the depreciation rate and remain larger than in the data. The calibrated parameters for the collateral constraints have increased to some extent for both SOEs and private firms, and the implied misallocation loss has decreased from 17.4% to 12.4% with the depreciation rate increasing to 0.10. Nonetheless, it remains true that private firms face more financial constraint than SOEs (see rows 4 and 5 in table 6 for the calibrated parameter values).

Heterogeneous Labor Elasticity and Return to Scale

The calibration results are also robust to some variations in the labor elasticity (α) and return to scale (η) (see column (7) in table 5). The motivation for varying labor elasticity and return to scale is that private firms are much smaller and more labor intensive than SOEs in the data, therefore they may have different production technologies (i.e. different production function parameters). When production is less capital intensive, the negative impact of a financial constraint on productivity is expected to be smaller. Therefore as a robustness check, the elasticity of labor is increased from 2/3 to 0.75 and the return to scale from 0.85 to 0.90 for private firms but the parameter values remain unchanged for SOEs. Again, the calibration results are similar (with good match to the targeted data moments) and the implied TFP loss reduces to 12.7%.

[41] The increased depreciation rates remain in the reasonable range commonly used by other studies such as Bartelsman, Haltiwanger, and Scarpetta (2013).

Heterogeneous Interest Rate

Private firms may not only face stricter collateral constraints but also pay higher interest rates for their borrowings than SOEs in Vietnam.[42] For example, many private firms borrow from the informal financial market, in which the borrowing costs are much higher than loans from banks. To take into account the different borrowing rates between SOEs and private firms, I first calculate the difference of the average products of capital between SOEs and private firms, which can be treated as a proxy for the difference in borrowing costs.[43] The calculated difference is -3.5%, suggesting that the borrowing costs for private firms are on average 3.5% higher than SOEs. When incorporating the heterogeneity in borrowing rates into the model, the calibrated misallocation loss from collateral constraints increases to 18% while the match of model is similar as before (see column (8) of table 5 and row 7 of table 6).

Outliers

To further reduce the potential impact of outliers, the top and bottom 2.5% (rather than 1%) of the data for the key variables are trimmed off and the data moments are calculated again for calibration. The standard deviations for output, capital, labor and their growth are now lower but the persistence remains similar (see column (9) of table 5). The microeconomic implications of the calibrated model with the new data moments are similar as before but the implied TFP loss by the model is smaller (13.7% versus 17.4%). This is reasonable as the standard deviations of output and output growth are smaller when the outliers (top and bottom 2.5%) are removed. Therefore the calibration results with the original data are to some extent affected by outliers but the efficiency loss from financial constraints is still large (see row 8 of table 6).

Sample Selection

Sample selection bias may remain a concern. Therefore rather than using the 6-year moving windows of the panel census, I calculate data moments from 4-year moving windows of the panel so that a larger sample of data is used for calibration (thus the autocorrelation of horizon five is no longer used to identify the autocorrelation coefficient).[44] Again the match to the new

[42] This is also another form of capital market distortion.

[43] The APKs are calculated from the estimated Cobb-Douglas production function using census data (2000-2009) from Vietnam.

[44] In this case only firms appearing less than 4 years are dropped (compared to 6 years before). The firms appearing with at least 4 years of data take up 56% of the cleaned data. Hence sample selection bias is reduced to some extent.

(targeted and untargeted) data moments is similar as the benchmark case and the model-implied TFP loss from misallocation increases moderately from 17.4% to 19.1% (see column (10) of table 5 and row 9 of table 6).

Although increasing the depreciation rate improves the match of the model-implied standard deviation for capital growth and persistence of capital to those in the data, the above robustness checks fail to improve the match to the standard deviations of labor and labor growth. If the data for labor also suffers from measurement errors while the model does not take this into account, one should expect the variances for both labor and labor growth to be larger in the data than in the model. But actually I find that the opposite is true in the data. Overall, the model of establishment dynamics with heterogeneous collateral constraints fails to provide a good match to the standard deviations of labor and labor growth.

The presence of measurement errors (other than outliers) and capital adjustment costs makes it difficult to identify the impact of market distortions on aggregate productivity loss (Syverson 2004, Balasubramanian and Sivadasan 2009). Song and Wu (2014) develop a generalized average revenue product (ARP) approach to identify capital misallocation from capital adjustment costs and measurement errors, and find that the aggregate revenue losses from misallocation are 20% in China but virtually zero for large Compustat firms.[45] I perform some extra robustness checks below to take into account possible multiplicative measurement errors and capital adjustment costs. The corresponding results are presented in table 7.

Measurement errors

Measurement error in firm-level data is a ubiquitous challenge for empirical analyses (Bartelsman, Haltiwanger and Scarpetta 2013). If there are large measurement errors in the data, the model may wrongly attribute the variation from measurement errors to market distortions and hence exaggerate the misallocation loss. The impact of outliers is mitigated to some extent already as the top and bottom 1% (2.5%) of the data for the key variables were trimmed off before producing the data moments for calibration. But it is difficult to deal with other types of measurement errors.

[45] This Compustat sample consists of large manufacturing firms with sales above USD10 million in 2000 prices and more than 500 employees.

Here I assume a multiplicative classical measurement error in output, following a log normal distribution and uncorrelated over time. Further taking the log transformation of the observed output, it becomes:

$$y_{j,t} = y_{j,t}^* + \varepsilon_{j,t}, \varepsilon_{j,t} \sim N(\mu, \sigma_\varepsilon^2)$$

where $y_{j,t}, y_{j,t}^*$ are the observed and true output, and $\varepsilon_{j,t}$ is the classical measurement error in output ($y_{j,t}, y_{j,t}^*, \varepsilon_{j,t}$ are after log transformation).[46] Obviously, this multiplicative measurement error cannot be identified from the transitory productivity shocks (e). Instead, I assume that the measurement errors increase the variance of output by x. The standard deviation of the observed output can be readily calculated from the data and therefore the variance of true output without the multiplicative measurement error can be derived by dividing the variance of observed output by $1 + x$. Similarly, the variance of output growth without measurement errors ($\mathrm{var}(\Delta y_t^*)$) can be calculated. In principle, the multiplicative measurement errors do not affect the autocorrelations if the measurement errors are uncorrelated over time.[47] The model is calibrated again with the new data moments with x set to be 3% (see column (1) in table 7).[48] The microeconomic implications of the calibrated model are again similar as before (see columns (2) in table 7). Row 10 of table 6 presents the corresponding parameter values and the implied TFP loss. It is still true that private firms face more financial frictions than SOEs. The implied misallocation loss is 14.4% if the multiplicative measurement errors increase the variance of output by 3%.

Capital Adjustment Costs

So far the calibrated model assumes that there are no capital adjustment costs. The presence of capital adjustment costs in the data reduces the responsiveness of capital to productivity shocks, and firms may substitute labor for capital to capture positive productivity shocks if possible. Therefore, one would expect the standard deviations to be larger but the persistence to be lower for both output and capital, and the standard deviations for labor and labor growth to be lower in the data than the simulated moments by the model. One may wrongly attribute the adjustment

[46] Assume the notations are already rescaled by the permanent productivity component.
[47] See appendix A3 for the derivations of the variances of true output and output growth in the presence of multiplicative measurement errors on output.
[48] When x gets too large, the variance of output growth becomes small and close to zero. For example, when x is set to be 0.06, the derived variance of output growth is reduced to only 0.038. Therefore I set x to be 0.03.

frictions to capital market distortions if the adjustment frictions are not considered in the model. Indeed, the variation of capital growth implied by the model is found to be smaller than in the data whereas the variations of both labor and labor growth implied by the model are larger than in the data. Hence it is likely that the misallocation loss is exaggerated when the model does not take into account the capital adjustment frictions.

Midrigan and Xu (2014) control for capital adjustment frictions by assuming that capital is predetermined and hence is not responsive to the current period productivity shocks (capital is chosen before the realization of the productivity shocks) and the calibrated misallocation loss from financial frictions is reduced from 2.5% to less than 1%. I control for the adjustment frictions similarly by assuming that capital is predetermined in the model with heterogeneous financial frictions between SOEs and private firms. Here the difference of the average debt-to-capital ratios is set to be 0.12 and 0.06 respectively rather than 0.27 because using the latter for calibration may exaggerate the financial constraint gap between SOEs and private firms (see table 7 columns (3) and (4)). Nevertheless the results are robust to capital adjustment frictions (the last two rows of table 6) and the TFP loss is still large (16.1% and 15.5% respectively).

Table 5

Match of Data and Model Moments for Extended Baseline Model, With total capital

	(1) Data	(2) Model 1	(3) Model 2	(4) Model 3	(5) $\delta = .08$	(6) $\delta = .10$	(7) $\alpha = .75, \eta = .90$ for private firms	(8) $\Delta r = -.035$[+]	(9) trim off 2.5%		(10) Moving panel in 4 years	
Panel A: Match of Model and Data Moments Targeted												
SD output	1.77	1.82	1.79	1.80	1.78	1.76	1.77	1.79	1.66	1.67	1.68	1.70
SD output growth	0.63	0.57	0.61	0.63	0.62	0.61	0.62	0.61	0.54	0.53	0.68	0.67
Autocorrelation lag 1 output	0.94	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.95	0.95	0.92	0.92
Autocorrelation lag 3 output	0.89	0.89	0.88	0.87	0.88	0.89	0.88	0.88	0.90	0.89	0.87	0.83
Autocorrelation lag 5 output	0.86	0.86	0.84	0.84	0.85	0.87	0.86	0.84	0.87	0.86	----	----
Debt to output ratio	0.68	0.65	0.68	0.68	0.69	0.70	0.67	0.68	0.68	0.69	0.68	0.68
ΔmDtoK$_{sp}$*	0.27	0.27	----	----	0.27	0.27	0.27	0.27	0.24	0.24	0.28	0.28
ΔmDtoK$_{sp}$*	0.06	----	0.06	----	----	----	----	----	----	----	----	----
ΔmDtoK$_{sp}$*	0.12	----	----	0.12	----	----	----	----	----	----	----	----
Panel B: Match of Model and Data Moments Not Targeted												
SD capital	1.72	1.75	1.71	1.72	1.75	1.75	1.82	1.75	1.61	1.63	1.62	1.63
SD capital growth	0.35	0.14	0.18	0.19	0.24	0.30	0.13	0.15	0.30	0.16	0.37	0.17
SD labor	1.44	1.78	1.79	1.80	1.78	1.76	1.75	1.79	1.38	1.67	1.35	1.70
SD labor growth	0.38	0.59	0.61	0.63	0.62	0.61	0.62	0.61	0.31	0.53	0.40	0.67
Autocorrelation lag 1 capital	0.98	1.00	0.99	0.99	0.99	0.99	1.00	1.00	0.98	1.00	0.97	0.99
Autocorrelation lag 5 capital	0.92	0.96	0.96	0.96	0.96	0.95	0.98	0.97	0.92	0.96	----	----
Autocorrelation lag 1 labor	0.97	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.97	0.95	0.96	0.92
Autocorrelation lag 5 labor	0.91	0.85	0.84	0.84	0.85	0.87	0.86	0.84	.92	0.86	----	----

*: it's the difference of the average debt to capital ratio between SOEs and private firms. The raw and net differences of average debt to capital ratio (isolating the effects from firm sizes, sectors, and regions) between SOEs and private firms are .27 and .06 respectively, and I also present the calibration results with the difference of average debt to capital ratios equal to .12 to control for the possibility that there are larger fractions of private firms facing binding collateral constraints than SOEs; +: the interest rate for SOEs is 3.5% lower than the interest rate for private firms.

Table 6
Parameters Calibrated and TFP Loss for Extended Baseline Model, with total capital

	$\boldsymbol{\theta_s}$	$\boldsymbol{\theta_p}$	$\boldsymbol{\rho}$	$\boldsymbol{\sigma}$	$\boldsymbol{\sigma_z}$	Misallocation loss
Extended model, difference of avg. debt to capital ratio (=.27)	0.42	0.14	0.63	1.55	2.07	17.4%
Extended model, difference of avg. debt to capital ratio (=.06)	0.34	0.25	0.63	1.57	2.15	16.4%
Extended model, difference of avg. debt to capital ratio (=.12)	0.40	0.24	0.61	1.59	2.19	16.5%
$\boldsymbol{\delta = .08}$	0.54	0.14	0.55	1.51	2.25	15.8%
$\boldsymbol{\delta = .10}$	0.64	0.14	0.51	1.36	2.33	12.4%
$\boldsymbol{\alpha = .75, \eta = .90}$ ***for private firms***	0.35	0.07	0.54	1.75	1.94	12.7%
$\boldsymbol{\Delta r = -.035}$	0.42	0.14	0.60	1.60	2.11	18.1%
Trim off top and bottom 2.5%	0.46	0.19	0.64	1.36	1.93	13.7%
Moving panel in 4 years	0.45	0.15	0.62	1.73	1.56	19.1%
Multiplicative measurement error*	0.46	0.18	0.66	1.21	2.00	11.5%
Predetermined capital+	0.30	0.18	0.57	1.68	2.24	16.1%
Predetermined capital++	0.28	0.22	0.57	1.64	2.27	15.5%

*: assume that the multiplicative measurement error increases the variance of output by 5%; + and ++: the difference of average debt to capital ratios between SOEs and private firms used for calibration is equal to 0.12 and 0.06 respectively.

Table 7
Data and Model Moments for Extended Baseline Model, With total capital
Additional Robustness Checks

	Panel A: Match of Model and Data Moments Targeted			
	Data	Multiplicative measurement error	Predetermined capital	Predetermined capital
	(1)	(2)	(3)	(4)
SD output	1.73	1.66	----	----
SD output growth	0.31	0.46	----	----
SD output	1.77	----	1.78	1.78
SD output growth	0.63	----	0.63	0.62
Autocorrelation lag 1 output	0.94	0.96	0.94	0.94
Autocorrelation lag 3 output	0.89	0.91	0.88	0.88
Autocorrelation lag 5 output	0.86	0.88	0.85	0.85
Debt to output ratio	0.68	0.69	0.69	0.68
ΔmDtoK$_{sp}$	0.27	0.27	----	----
ΔmDtoK$_{sp}$	0.12	----	0.12	----
ΔmDtoK$_{sp}$	0.06	----	----	0.06
	Panel B: Match of Model and Data Moments Not Targeted			
SD capital	1.72	1.63	1.71	1.70
SD capital growth	0.35	0.12	0.13	0.13
SD labor	1.44	1.66	1.78	1.78
SD labor growth	0.38	0.46	0.63	0.62
Autocorrelation lag 1 capital	0.98	1.00	1.00	1.00
Autocorrelation lag 5 capital	0.92	0.97	0.97	0.97
Autocorrelation lag 1 labor	0.97	0.96	0.94	0.94
Autocorrelation lag 5 labor	0.91	0.88	0.85	0.85

Note: ΔmDtoK$_{sp}$ is the difference of average debt to capital ratio between SOEs and private firms.

To sum up, the calibrated baseline model and its extension provide a good match to the key data moments targeted and the standard deviation of capital calculated from the enterprise census data (2000-2009). But the match by the model to other data moments such as the standard deviations of capital growth, labor, and labor growth, and the persistence of capital and labor is less than perfect. The model is able to generate a large TFP loss from misallocation. Private firms face much stricter financial frictions than SOEs. The misallocation losses increase with the gap of the financial constraints between SOEs and private firms. The results are robust to variations in parameter values, heterogeneity in borrowing rates, potential sample selection bias, and some other modifications in the model. The calibration results are robust to measurement errors and frictions that hinder the producer's ability to respond to shocks (e.g. capital adjustment costs).

4.4 TFP Changes from Varying Calibrated Parameters

Previously I explored the efficiency losses from financial constraints by parameterizing a model of establishment dynamics with collateral constraints to match the salient features of the panel census data. In this subsection I calculate instead what the efficiency gain/loss would be from varying one or more of the *calibrated* parameters, e.g. the parameters governing the strength of collateral constraints, and the standard deviation and persistence of the productivity shocks. The variation tells how TFP would change if one or more of the key parameters change while leaving others unchanged.

I first investigate how TFP would change in response to the variation in the parameters governing the degrees of collateral constraints for both SOEs and private firms (allocative efficiency remains the same as in the original economy). The results are presented in table 8. Previous calibration results show that both SOEs and private firms face severe collateral constraints and more so for private firms, with the corresponding misallocation loss being 17.4%. If the collateral constraints are completely removed for both types of firms ($\theta_s = \theta_p = 1$), the efficiency loss is reduced to zero as expected. If the degrees of financial constraints are reduced to 0.85 ($\theta_s = \theta_p = .85$), the TFP loss from misallocation is 3.1%. When the collateral constraints in Vietnam (for both SOEs and private firms) would be the same as in South Korea ($\theta_s = \theta_p = .57$),[49] the resulting TFP loss is 10% in a closed economy. If private firms would face the same degrees of financial constraint as SOEs in Vietnam ($\theta_s = \theta_p = .42$), the resulting GDP loss would be 13.5%. What are the TFP losses if the financial constraints become more severe? The hypothetical experiments show that when the parameters for the borrowing constraints of SOEs are reduced to 0.30 while the financial constraints experienced by private firms are the same as in the original economy ($\theta_s = .30, \theta_p = .14$), the implied TFP loss is 17.1%, slightly smaller than the 17.4% in the original economy. If SOEs experience the same degree of financial constraints as private firms in the original economy ($\theta_s = \theta_p = .14$), the resulting TFP loss becomes 16.6%. When financial constraints are hypothetically becoming more severe for SOEs, they would reduce their demands for capital, releasing more capital in the economy. Hence there is more capital available for private firms to use. Private firms have been shown to be more efficient than SOEs when controlling for firm sizes. Hence the resulting TFP

[49] This value of 0.57 is taken from Midrigan and Xu (2014).

losses become smaller compared to the original economy when the collateral constraint parameter for SOEs becomes smaller. When the parameters for the collateral constraints are reduced further for both ownership types (e.g. $\theta_s = \theta_p = .05$), the resulting TFP loss starts rising again.

Table 8
TFP Losses from Varying Calibrated Parameters

Parameters	ΔTFP
$\boldsymbol{\theta_s = .05, \theta_p = .05}$	16.7%
$\boldsymbol{\theta_s = .14, \theta_p = .14}$	16.6%
$\boldsymbol{\theta_s = .42, \theta_p = .14}$	17.4%
$\boldsymbol{\theta_s = .42, \theta_p = .42}$	13.5%
$\boldsymbol{\theta_s = .57, \theta_p = .57}$	10.0%
$\boldsymbol{\theta_s = .85, \theta_p = .85}$	3.1%
$\boldsymbol{\theta_s = 1, \theta_p = 1}$	0%
$\boldsymbol{\rho = .63 \rightarrow \rho = .85}$	28.7%
$\boldsymbol{\sigma = 1.55 \rightarrow \sigma = 2.35}$	31.1%

Misallocation loss increases with both the persistence and the variance of productivity shocks. When the persistence of the productivity shocks is increased from .63 to .85 (as it takes time for producers to accumulate assets), the loss from misallocation is as large as 28.7%. However, in the long run with persistent enough productivity shocks, productive producers can accumulate assets for production and will grow out of financial constraints and the TFP loss may become smaller. Similarly, if one further increases the standard deviation of the transitory productivity shocks from 1.55 to 2.35, the misallocation loss for the economy is increased from 17.4% for the original economy to as high as 31.1%. Hence large uncertainty has a negative impact on aggregate productivity. This is intuitive as firms are less capable of accumulating retained earnings and are less willing to investment when uncertainty is large. Overall, misallocation loss increases with the persistence and the variance of the productivity shock.

5 Conclusion and Discussion

This paper investigates whether financial frictions can generate large TFP losses and whether SOEs and private firms face different degrees of collateral constraints, using data from a transition country Vietnam featured by piecemeal (incomplete) economic reforms. The paper investigates the capital misallocation using a model of establishment dynamics with collateral constraints from Midrigan and Xu (2014) with an extension to allow for different degrees of financial frictions experienced by SOEs and private firms. The model is then parameterized to match the key data moments calculated from the 6-year moving windows of panel census data (2000-2009) for manufacturing firms. The parameterized model provides a good match to the targeted data moments but the match to other untargeted data moments appear less than fully satisfactory. The calibration results show that private firms face stricter financial frictions than SOEs, and that the misallocation loss is large ranging from 11.5% to 19.1%. The results are robust to some variations in technology and preference parameters, measurement error, potential sample selection bias, and heterogeneity in borrowing rates between SOEs and private firms, as well as frictions that hinder firms' responses to productivity shocks such as capital adjustment costs. For a given level of financial development, the misallocation losses increase with the financial constraint gap between SOEs and private firms. The large TFP losses found in this paper in Vietnam are in contrast to the small misallocation losses for South Korea in Midrigan and Xu (2014).

The limitation of this paper is that it focuses on misallocation among existing firms and does not consider distortion on entry. Many literatures have shown already that the efficiency losses from entry distortion are potentially large. Entry distortions are expected to be severe in Vietnam. A large number of firms (e.g. household enterprises) are actually operating informally and not registered in any tax office, which is considered as one important type of entry distortions. Moreover, the efficiency losses from misallocation may well be larger in a dynamic framework. Last but not least, the model is simple in the sense that all SOEs (and all private firms) face the same borrowing ceiling (the upper bound of their debt-to-capital ratios). Large firms tend to have higher debt-to-capital ratios than small firms and firm size is found to be positively correlated with ownership. But this scale effect on debt-to-capital ratios is not taken into account in the modeling. One could further model the collateral constraint parameters as a function of firm scale to control for any possible scale effects. In this case, firms will have heterogeneous borrowing ceilings. I leave this for future analysis.

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Appendices

A1 Data Cleaning and Calculation of Data Moments for Calibration

A1.1. Data Cleaning

The data for use is the enterprise census (2000-2009) in Vietnam, collected every year between March and May of the following year (2001-2010) by the general statistical office (GSO). Recall bias can be very large, especially for the beginning of year values (with the recall period more than one year). Therefore the data cleaning is performed mainly on the end of year values (if available) and data moments are then calculated for calibration. For more information on the enterprise census data, one can go back to chapter 3 and appendix A3. I first illustrate the data cleaning in detail below.

The key variables used for producing data moments include: ownership, value added, and the end of year values for fixed and total capital, labor, equity, and debt. Some of the panel identifiers used for data merging over time is inconsistent. Different firms may be recorded wrongly with the same panel identifiers or the same firms may be wrongly given different panel identifiers. So the observations with duplicates in terms of key variables (capital, labor, value added, debt, and equity) in the data within the same year but with different panel identifiers are deleted. Next, observations without time variation in the key variables are removed. The sectors of tobacco, coke and refined petroleum, office, accounting and computing machinery, and recycling with sector numbers 16, 23, 30, and 37 respectively are deleted due to small number of observations and concentration of ownership by most firms. Foreign firms are dropped as the analysis focuses on SOEs and private firms.[50]

Furthermore, the top and bottom 1% of the data for the key variables such as value added, output growth, capital growth, and labor growth, wages, sales, and the end of year fixed and total capital, labor, and debt, are trimmed off; observations with capital output ratio above 1000 or below .05 are removed; and also firms appearing with gap or discontinuously are dropped.

Since the model for calibration is for firms in operation, ideally one should calculate data moments from a balanced panel. As the balance panel with 10 years of data covers less than 5% of the raw data, sample selection bias can be large. Autocorrelations of horizon one, three, and

[50] The data moments with or without foreign firms are quite similar

five for output are used for the identification of autocorrelation of productivity in Midrigan and Xu (2014), therefore at least 6 years of data are required. To reduce sample selection bias, I calculate data moments from 6-year moving windows of the census data rather than from a balance panel with 10 years. The idea is that I calculate key data moments from each of the 6-year moving window (2000-2005, 2001-2006, 2002-2007, 2003-2008, and 2004-2009).[51] The final data moments are the averages of the data moments calculated from the five moving windows. The data moments are not very different from the corresponding cross-sectional averages.[52]

In some robustness checks, data cleaning may be different. For example, instead of 6-year moving windows of panels, data moments are also calculated from panels of 4-year moving windows (dropping firms with less than 4 years); and the top and bottom 2.5% (rather than 1%) of the data for the key variables are trimmed off to reduce the bias from outliers.

Data on firm sales, labor compensation, and net profits are not available every year for material and energy costs.[53] Thus value-added is calculated as the sum of net profit, labor compensation, indirect taxes, and depreciation. Measurement errors can be quite large for value-added. This is because profit data often contain large measurement errors. Data on depreciation can be noisy as it is calculated from the difference between the end of period accumulated depreciation and the beginning of period accumulated depreciation (if the data is missing, depreciation is calculated as the multiplication of fixed capital stock and an average depreciation rate of 8% inferred from the data).

A1.2. Calculation of Data Moments

Next I illustrate the calculation of the key data moments (e.g. the standard deviations of output and output growth; persistence of output; the standard deviations of labor and labor growth and capital and capital growth; debt-to-capital ratio, difference of the average debt to capital ratio between SOEs and private firms, et cetera). First I calculate the data moments from each moving window and then take the averages of the data moments from all moving windows.

[51] Each moving window consists of a balanced panel with 6 years of data.
[52] Note that autocorrelation coefficients cannot be calculated from cross-section data.
[53] The data on material and energy costs are only available in some years but not all 10 years.

I use the difference of the average debt-to-capital ratios between SOEs and private firms as well as the aggregate debt-to-output ratio to identify the collateral constraint parameters (θ_s and θ_p). The model implied debt-to-capital ratio is in the range of [0,1]. But in the data, most of the observations have the average debt-to-capital ratios well above 1 when capital is measured as fixed assets. But when capital is measured with total assets, the debt-to-capital ratios are mostly between 0 and 1. Therefore I use total capital rather than fixed capital to calculate relevant data moments.

There are three different ways to calculate the data moments:

1) Directly calculate from the panel data (cleaned unbalanced panel with 6 years of data)
2) Calculate data moments from each year and then take the average of the cross-sectional averages from all years (cross-sectional averages, except for persistence)
3) Calculate data moments from each 6-year moving window of the census data and then take the averages of the data moments across the moving windows

I calculate data moments from the above 3 approaches and check whether there are large differences (see table A1). The standard deviations of output, capital and labor calculated from moving windows are between the values calculated from panel and cross-sectional data while the standard deviations of output/capital/labor growth are the smallest among three calculations from panels of moving windows. The autocorrelation coefficients are similar whether calculated from the panel or 6-year moving windows of the panel. The debt-to-capital ratio and the capital-labor-ratio are also similar. Hence the data moments calculated from the moving windows are not very different from data moments from unbalanced panel and from cross-sectional averages. Therefore I use the data moments calculated from the 6-year moving windows for calibration.

Table A1
Data Moments Vietnam Census 2000-2009

		With total capital		
		Panel	Cross Section	Moving Panel
Output	SD	1.789	1.753	1.771
	SD growth	0.629	0.627	0.627
	Autocorrelation lag 1	0.939	----	0.938
	Autocorrelation lag 3	0.896	----	0.892
	Autocorrelation lag 5	0.858	----	0.857
Capital	SD	1.749	1.696	1.723
	SD growth	0.363	0.368	0.351
	Autocorrelation lag 1	0.979	----	0.979
	Autocorrelation lag 3	0.946	----	0.946
	Autocorrelation lag 5	0.911	----	0.915
Labor	SD	1.449	1.428	1.443
	SD growth	0.385	0.388	0.377
	Autocorrelation lag 1	0.965	----	0.966
	Autocorrelation lag 3	0.931	----	0.934
	Autocorrelation lag 5	0.903	----	0.910
Debt to Capital	Private	0.292	0.302	0.297
	SOEs	0.559	0.555	0.567
Debt to Output	Debt GDP ratio	0.68	0.68	0.68

Data source: Vietnam census 2000-2009; firms with gaps and firms with less than 6 years are removed after the initial data cleaning; SD stands for standard deviation.

A2 Dealing with Sample Selection Bias

Although the data moments for calibration are calculated from the 6-year moving windows of the panel, the sample selection bias may still be large. As a first step, I calculate the key data moments from different samples to see if they are very different from one another or not. In principle, if the data moments are very different, then one should worry about the sample selection bias.

Below I present the key data moments calculated from different samples. The data moments from columns (1)-(4) respectively are calculated from: 6-year moving windows (removing firms with less than 6 years of data); 4-year moving windows (removing firms with less than 4 years of data, so the autocorrelation of horizon 5 will not be used for calibration to identify the autocorrelation of output); 6-year moving windows but excluding year 2000, 2001, and 2009; and finally the cleaned unbalanced panel.

The variations of the data moments calculated from different samples are not too much (see table A2). Hence sample selection bias may not a large concern here, at least regarding the key data moments that we are interested in. Therefore I proceed to use the data moments calculated from the 6-year moving windows of the panel (2000-2009) for the calibration of the model in the paper.

Table A2
Data Moments from Various Samples, With total capital, excluding foreign firms

	(1)	(2)	(3)	(4)
	Panel A: Match of Model and Data Moments Targeted			
SD output	1.77	1.68	1.86	1.59
SD output growth	0.63	0.68	0.60	0.76
Autocorrelation lag 1 output	0.94	0.92	0.95	0.90
Autocorrelation lag 3 output	0.89	0.87	0.91	0.87
Autocorrelation lag 5 output	0.86	-----	0.86	0.86
Debt to output ratio	0.68	0.68	0.68	0.68
ΔmDtoK$_{sp}$	0.27	0.29	0.26	0.26
	Panel B: Match of Model and Data Moments Not Targeted			
SD capital	1.72	1.62	1.84	1.49
SD capital growth	0.35	0.37	0.35	0.41
SD labor	1.44	1.35	1.52	1.24
SD labor growth	0.38	0.40	0.38	0.43
Autocorrelation lag 1 capital	0.98	0.97	0.98	0.97
Autocorrelation lag 3 capital	0.95	0.94	0.95	0.94
Autocorrelation lag 5 capital	0.92	-----	0.92	0.92
Autocorrelation lag 1 labor	0.97	0.96	0.97	0.95
Autocorrelation lag 3 labor	0.93	0.92	0.92	0.94
Autocorrelation lag 5 labor	0.91	-----	0.91	0.90

A3 Deriving the Variances of Output and Output Growth before Multiplicative Measurement Errors

Assume a multiplicative classical measurement error on output following log normal distribution and uncorrelated over time. Taking the log transformation of the observed output we have:

$$y_t = y_t^* + \varepsilon_t, \varepsilon_t \sim N(\mu, \sigma_\varepsilon^2)$$

where y_t, y_t^* are the log of observed and true outputs, and ε_t is the log of classical measurement error on output. Next I present how to calculate the variances of true output and output growth.

Suppose the measurement errors increase the variance of true outputs by x ($\frac{var(\varepsilon_t)}{var(y_t^*)} = x$). The variance of observed outputs is written as:

$$var(y_t) = var(y_t^* + \varepsilon_t) = var(y_t^*) + var(\varepsilon_t) = (1 + x) * var(y_t^*)$$

Therefore the variance and standard deviation for the outputs before measurement errors become:

$$\mathrm{var}(y_t^*) = \frac{\mathrm{var}(y_t)}{1+x}, \mathrm{sd}(y_t^*) = \frac{\mathrm{sd}(y_t)}{\sqrt{1+x}}$$

Output growth is defined as $\Delta y_t = \Delta y_t^* + \Delta\varepsilon_t$. Since I assume that ε_t is uncorrelated over time and randomly drawn from log normal distribution, hence

$$\mathrm{var}(\Delta\varepsilon_t) = \mathrm{var}(\varepsilon_t - \varepsilon_{t-1}) = 2 * \mathrm{var}(\varepsilon_t)$$

Therefore the variance and standard deviation of true output growth are derived as follows:

$$\mathrm{var}(\Delta y_t) = \mathrm{var}(\Delta y_t^*) + \mathrm{var}(\Delta\varepsilon_t) = \mathrm{var}(\Delta y_t^*) + 2 * \mathrm{var}(\varepsilon_t)$$

$$\mathrm{var}(\Delta y_t^*) = \mathrm{var}(\Delta y_t) - \frac{2x}{1+x}\mathrm{var}(y_t)$$

$$\mathrm{sd}(\Delta y_t^*) = \sqrt{\mathrm{var}(\Delta y_t) - \frac{2x}{1+x}\mathrm{var}(y_t)}$$

The multiplicative measurement errors in output do not affect the autocorrelation coefficient:

$$\rho_1 = \mathrm{corr}(y_t, y_{t-1}) = \mathrm{corr}(y_t^* + \varepsilon_t, y_{t-1}^* + \varepsilon_{t-1}) = \mathrm{corr}(y_t^*, y_{t-1}^*)$$

A4 Programming Details for Solving the Model

This appendix documents the programming details for the extended baseline model with MATLAB. In order to run the programs in the relevant folders, one has to first download and install the toolbox ‘CompEcon’ (into MATLAB toolbox) written by Miranda and Fackler (2011) (available on their websites). I have also utilized the programming codes of Midirgran and Xu (2014) as a key reference (their codes are available on the AEA website).

The details of the model can be found in the paper. For ease of understanding, I briefly illustrate the dynamic problem for producers (same for SOEs and private firms except that they face different collateral constraints):

$$V(a^m, e) = \max_{a^{m\prime}, c^m} \log(c^m) + \beta EV(a^{m\prime}, e')$$

Subject to a budget constraint and a borrowing constraint:

$$c^m + a^{m\prime} = \pi(a^m, e) + (1+r)a^m$$

$$k \leq \frac{1}{1-\theta_x} a^m, x = s, p$$

As for workers, they optimize lifetime utility (same as producers):

$$V(a^w, \nu_i) = \max_{a^{w\prime}, c^w} \log(c^w) + \beta \sum_{j \in n^w} p_{i,j} V\left(a^{w\prime}, \nu_j\right)$$

subject to a budget constraint $c^w + a^{w\prime} = W\nu + (1+r)a^w$. Consumption can be substituted out using the budget constraint and the dimension of the optimization problem is reduced.

Computational Issues

The value function V is approximated with spline approximation. The transitory productivity shock e follows AR(1) process but can be discretized by a Markov process with finite states (9). The optimal choices of capital and labor are static and can be solved off the dynamics for given collateral constraints. The multipliers (μ) associated with the collateral constraints plus interest rate measure the shadow values of external financing and depend on savings and the productivity shock. Specifically, they are decreasing in savings/assets and increasing in the productivity shock. The dynamic program is solved using projection methods. The details of the projection methods and the codes can be found in textbook "Applied Computational Economics and Finance". The optimal saving decision rule is obtained using the golden search method. The optimization and dynamic program problems for workers are solved similarly.

The Stationary Distribution for Markov Chain

Next I briefly illustrate how to calculate the stationary distribution of the Markov process. One can compute the stationary distribution by a brute force method. Suppose P is the transition matrix, take P^T for a large number of T, say 5000. Then one will get back a matrix with identical rows that are equal to the stationary distribution of the Markov chain. A neater approach is to use Matlab to compute the eigenvalues and vectors of P. First compute the matrix of eigenvalues and eigenvectors for P^T. In Matlab, $[V, D] = \mathrm{eig}(P^T)$ gives a matrix of eigenvectors V and a diagonal matrix D whose entries are the eigenvalues of P^T. Since P is a transition matrix, one of the eigenvalues is 1. Next pick the column of V associated with the eigenvalue 1. Finally, normalize the eigenvector to sum to one to obtain the stationary distribution.

About Simulation

Once the optimal choices for capital, labor, and savings are obtained, one can simulate data using these decision rules. First, one should set the simulation period long enough to get rid of the impact from initial values and to obtain stationary distributions. Therefore I set the simulation period to be 56 years and only the last 6 years of the simulated data are used to calculate the moments for calibration. The second important thing is to make sure that the sample size of the simulation is sufficiently large (N=40000).

With the stationary transition probability matrix and the initial guesses for the productivity shocks, one can simulate the productivity shocks over time. Next with the simulated productivity shocks and the initial guess of savings, one can infer the optimal savings in each period, using the decision rule for savings obtained from the dynamic program. To get rid of the influence of initial conditions, I only save the last 6 years of simulated data for calculating moments for matching (savings and productivity shocks).

With the simulated data for savings and productivity shocks, I can calculate the multipliers associated with the collateral constraints and then calculate the optimal choices of capital and labor (which depends the multipliers). Therefore outputs can be calculated with the production technology assumed. The debt or borrowing is inferred from the difference between savings and capital. The standard deviations and persistence of the simulated outputs, capital, labor, and the standard deviation of their growth thus can be readily calculated from the simulated data.

The underlying structural parameters can be updated by minimizing the weighted distance between the model implied moments from the simulation and the data moments. This procedure is repeated till the model implied moments are close enough to the data moments.

A5 Notes on Rescaling Variables in the Model by exp(z)

In order to reduce the dimensionality of the problem, I rescale all variables in the model by $\frac{1}{\exp(z)}$ and denote the rescaled variables by their corresponding lower case. For example,

$$l^m = \frac{L^m}{\exp(z)}, k = \frac{K}{\exp(z)}, c^m = \frac{C^m}{\exp(z)}, a^m = \frac{A^m}{\exp(z)}$$

Next I demonstrate the rescaling of other variables that are less direct. First is the output,

$$y = \frac{Y_t}{\exp(z)} = \frac{\exp(z+e_t)^{1-\eta}\,({L_t^m}^{\alpha} K_t^{1-\alpha})^{\eta}}{\exp(z)} = \frac{\exp(z+e_t)^{1-\eta}\,({L_t^m}^{\alpha} K_t^{1-\alpha})^{\eta}}{(\exp(z))^{1-\eta}(\exp(z))^{\eta}}$$

$$= \exp(e_t)^{1-\eta}\,({l_t^m}^{\alpha} k_t^{1-\alpha})^{\eta}$$

The profit is equal to $Y - WL^m - (r+\delta)K$ and the rescaled profit becomes:

$$\pi(a,e) = \exp(e)^{1-\eta}\,({l^m}^{\alpha} k^{1-\alpha})^{\eta} - Wl^m - (r+\delta)k$$

Next I demonstrate how to transform the budget constraint with rescaled variables. The original budget constraint is:

$$C^m + K' - (1-\delta)K = Y - WL^m - (1+r)D + D'$$

First reorganize the budget constraint by moving D' to the left side and $(1-\delta)K$ to the right side (prime denotes next period values), the above equation is reorganized as:

$$C + \underbrace{K' - D'}_{={A^m}'} = Y - WL^m - (r+\delta)K + (1+r)\underbrace{(K-D)}_{=A^m}$$

Next multiply the above equation by $\frac{1}{\exp(z)}$ on both sides, one arrives at

$$c^m + {a^m}' = \pi(a^m, e) + (1+r)a^m$$

Below I further demonstrate the equivalence of the asset market clearing condition and the aggregate budget constraint. But first I would like to clarify that the upper cases (e.g. C^m, C^w, L, K, Y, A^m, A^w) used from here onward denote aggregate values.

In equilibrium, the aggregate budget constraints for producers and workers can be expressed as:

I. $C^m + {A^m}' = \Pi + (1+r)A^m$

II. $C^w + {A^w}' = WL + (1+r)A^w$

where $\Pi = Y - WL - (r+\delta)K$ is the aggregate profits. The aggregate budget constraint for the whole economy is that aggregate spending from producers and workers should be equal to aggregate output:

III. $C^m + I^m + C^w = Y$

And the aggregate borrowing from producers should be equal to the aggregate savings from workers as well, namely $A^w = D, {A^w}' = D'$. The other relationship is that the aggregate savings of producers is equal to the aggregate capital stock minus aggregate borrowing: $A^m = K -$

D.Next, I demonstrate the equivalence of the asset market clearing condition with the aggregate budget constraint. The asset market clearing condition is:

$$\mathrm{A^{m\prime}} + \mathrm{A^{w\prime}} = \mathrm{K'}$$

Using the budget constraints I for producers and II for workers to substitute out both $\mathrm{A^{m\prime}}$ and $\mathrm{A^{w\prime}}$, one arrives at the following:

$$\overbrace{\mathrm{Y - WL - (r+\delta)K + (1+r)(K-D) - C^m}}^{\mathrm{A^{m\prime}}} + \overbrace{\mathrm{WL + (1+r)A^w - C^w}}^{\mathrm{A^{w\prime}}} = \mathrm{K'}$$

Using the condition that $\mathrm{A^w = D}$, and $\mathrm{A^m = K - D}$, the above equation can be simplified as:

$$\mathrm{Y + (1-\delta)K - C^m - C^w = K'}$$

Moving all other terms in the left hand side of the above equation except Y to the right hand side, the equation can be rewritten as:

$$\mathrm{C^m + I^m + C^w = Y}$$

which is exactly the aggregate budget constraint for the whole economy.

A6 Distribution of Debt-to-Capital Ratios across Ownership, Sizes, Sectors, and Regions

The raw difference of the average debt-to-capital ratios between SOEs and private firms is 0.27 in the data. But private firms are different from SOEs in the data. For example, SOEs are in general much larger than private firms. SOEs may concentrate in different sectors and/or regions from private firms. Hence it's likely that the firm-level difference of the average debt-to-capital ratios between SOEs and private firms may reflect differences other than ownership. Therefore I perform a regression of the debt-to-capital ratios on ownership dummies, controlling for size dummies (model 2) and sector and region dummies (model 3). The results are presented in table A3. Indeed the difference of the average debt-to-capital ratios between SOEs and private firms is reduced from 0.27 to 0.06 after controlling for sizes (and sectors and regions). The coefficients for size dummies (medium and large firms) are positive and significant and much larger than the coefficient for SOEs dummy.

In the data private firms are much smaller than SOEs in terms of labor, capital, and sales. Firms in Vietnam are required to provide tangible collaterals for borrowing, especially for private firms, and therefore they may experience stricter financial constraints than SOEs. Moreover, it is likely that there are a larger fraction of private firms facing binding collateral constraints than SOEs. In such case, the raw difference of the average debt-to-capital ratios (0.27) may be smaller than the actual financial constraint gap ($\theta_s - \theta_p$). But it's unclear whether this effect (more private firms facing binding constraints) dominates the size effect or not, hence there is no clear upper bound. The speculation is that size effect is more likely to dominate the other effect with more private firms facing binding collateral constraints. Hence the raw difference of the average debt-to-capital ratios (0.27) can be treated as the upper bound. The net difference of the average debt-to-capital ratios between SOEs and private firms can be treated as the lower bound of the actual financial constraint gap ($\theta_s - \theta_p$).

Table A3
Regressions of Debt-to-Capital Ratios

	SOEs	Medium	Large	Constant
model 1	0.267	0.000	0.000	0.292
model 2	0.059	0.260	0.318	0.238
model 3	0.059	0.205	0.278	0.224

Note: model 1 is the basic regression of debt to capital ratio on ownership dummies; model 2 regresses debt to capital ratio on ownership and size dummies; and model 3 regresses debt to capital ratio on ownership, size, sector, and region dummies.