

Finance, Managerial Inputs, and Misallocation[†]

By CHAORAN CHEN, ASHIQUE HABIB, AND XIAODONG ZHU*

In standard macrofinance models, financial constraints mainly affect small or young firms but not large or old ones due to the self-financing mechanism, and the dispersion of marginal revenue product of capital (MRPK) of a firm cohort is less persistent than in the data. We extend a standard model by allowing firms to hire managers, and large firms hire disproportionately more managers, consistent with data. In our model, financial constraints and the dispersion of MRPK persist, and even large firms are likely to be constrained. The productivity loss from financial frictions is also substantially amplified. (JEL D24, D25, G32, L25, M10, O16, P31)

A recent literature argues that misallocation of production factors, especially the misallocation of capital, is a main reason for low total factor productivity (TFP) in developing countries (Restuccia and Rogerson 2008; Hsieh and Klenow 2009), which in turn is the main source of per capita income differences (Klenow and Rodríguez-Clare 1997; Caselli 2005). While financial frictions are a natural source of capital misallocation, the literature assessing the quantitative importance of this channel on aggregate TFP finds small effects (Buera, Kaboski, and Shin 2011; Moll 2014; Midrigan and Xu 2014). The literature typically models financial frictions by assuming that firms face collateral constraints. In these models, the quantitative effects of collateral constraints are small due to the incentive of productive firms to undo them through self-financing.¹ These models' predictions are also at odds with the imprint of misallocation across both the firm size distribution and the firm life

*Chen: Department of Economics, York University (email: chenecon@yorku.ca); Habib: International Monetary Fund (email: ahabib@imf.org); Zhu: Faculty of Business and Economics, University of Hong Kong (email: xdzhu@hku.hk). Peter Klenow was coeditor for this article. Comments from three anonymous referees helped improve the paper. We also thank Stephen Ayerst, Loren Brandt, Davin Chor, Ying Feng, In-Hwan Jo, Lin Ma, Virgiliu Midrigan, Andreas Pollak, Diego Restuccia, Juan Sanchez, Michael Song, and Daniel Yi Xu, as well as conference and seminar participants at the Canadian Economics Association Meetings, China Conference on Growth and Development, China International Conference in Macroeconomics, Chinese University of Hong Kong (Shenzhen), Econometric Society Asia Meeting, Fudan University, Midwest Macro Conference, National University of Singapore, Peking University, Shanghai University of Finance and Economics, Sun Yat-Sen University, University of Alberta, and York University for useful feedback. Chen gratefully acknowledges support from the Social Sciences and Humanities Research Council of Canada (430-2020-00976). All errors are our own. The views expressed here are those of the authors and should not be attributed to the International Monetary Fund or its executive board or management.

[†]Go to <https://doi.org/10.1257/aeri.20220285> to visit the article page for additional materials and author disclosure statement(s).

¹The literature does find larger effects of financial constraints at the extensive margin on entry decisions, technology adoption, and sectoral choice of firms. Our focus in this paper, however, is on the misallocation of production factors among incumbent firms.

cycle in developing countries. While firm-level evidence from developing countries suggests that large firms may face more severe distortions (Hsieh and Olken 2014), these models predict that financial constraints distort mainly small or young firms. Furthermore, while data suggest that the dispersion in marginal revenue product of capital (MRPK) for a cohort of firms is highly persistent over time (Banerjee and Moll 2010; David and Venkateswaran 2019), these models predict a short dispersion half-life as self-financing quickly undoes financial frictions (Moll 2014).

A common assumption used in financial constraint models is that firm-level TFP is exogenous and not affected by financial frictions. Recently, however, a growing literature emphasizes that firms can improve their TFP by investing in management practices or hiring professional managers (Bloom and Van Reenen 2007, 2010; Guner, Parkhomenko, and Ventura 2018). The literature has also offered evidence that managerial inputs are nonhomothetic in firm size: large firms hire disproportionately more managers (Grobovšek 2020; Akcigit, Alp, and Peters 2021). In this paper, we introduce such firm expenditures on managerial inputs to the standard collateral constraint model used by Midrigan and Xu (2014) and reexamine the quantitative effects of financial frictions on capital misallocation and aggregate TFP. We show that our model with nonhomothetic managerial inputs can better match financial constraints faced by firms across both the firm size distribution and the firm life cycle in the data and amplify the impact of financial frictions on aggregate productivity.

The logic of our argument is as follows. Consider a firm with a productive blueprint but little collateral in a country with weak financial development and, consequently, tight collateral requirements. Initially, the firm can only operate on a small scale due to its limited collateral, which yields an MRPK that is substantially higher than the interest rate. This high MRPK then incentivizes the firm to save toward relaxing the collateral constraint, and as it does so its MRPK declines. This is the standard self-financing channel that mitigates the impact of collateral constraints on aggregate TFP, limits distortions to small firms and young firms, and generates quantitatively fast-resolving MRPK dispersion for a cohort of firms. We introduce the option to hire professional managers. Such an option has two implications. First, in our framework, as in the data, expenditures on hiring managers are nonhomothetic, with large firms hiring disproportionately more managers. Therefore, as a firm becomes larger by accumulating collateral and physical capital, its expenditure share on managers increases and its profit margin and hence the ability to self-finance declines. Second, as a firm hires more managers, its elasticity of scale increases, which in turn increases capital demand and hence the MRPK. These new channels partially offset the speed at which the self-financing channel undoes collateral constraints. With nonhomothetic managerial inputs, the MRPK dispersion of a firm cohort is more persistent and large firms and old firms are more likely to be financially constrained.

To quantitatively assess the contribution of our novel channels, we compare our benchmark model with nonhomothetic managerial inputs and an otherwise identical model but without managerial inputs. To ensure a fair comparison, we calibrate both models to match exactly the same set of moments commonly chosen in the literature using firm-level data from China. Particularly, we calibrate the collateral constraint and productivity shock process such that in the steady state, both models generate the same debt-to-output ratio and output dispersion and autocorrelation—moments

used in Moll (2014) and Midrigan and Xu (2014), among others. We calibrate the management parameters to match the distribution of manager-to-worker ratio in the firm-level data—that is, large firms hire more managers per employee. Since our benchmark model has one more factor of input (managers), we make sure that both models have the same aggregate profit margin and capital share in the stationary equilibrium.

Comparing the results from the two calibrated models, we find that it takes twice as much time for a high-productivity but low-collateral entrepreneur to save up to the unconstrained level when we allow for nonhomothetic managerial inputs. The dispersion in MRPK of a cohort of firms is also more persistent in our model: it takes roughly twice as many periods for the cohort to eliminate 90 percent of its initial dispersion in MRPK through self-financing. Consequently, in the steady state, firms are more likely to face binding financial constraints in our benchmark model than in the model without managerial inputs and as a result the efficiency gain associated with eliminating the collateral constraint from our model (6.4 percent) is almost twice as large as that of the model without managerial inputs (3.7 percent).

We also highlight that the key to our results is that managerial inputs are nonhomothetic in firm size, consistent with the empirical evidence. If instead the production function is homothetic and the equilibrium manager-to-worker ratio is constant among firms, then allowing for managerial inputs would have no impact on the effects of collateral constraints, provided that the models are calibrated to match the aggregate capital share in the data. Given the central role of the nonhomotheticity, our results can be interpreted more broadly: allowing for other inputs, such as skilled labor or innovation efforts, that enter the production function nonhomothetically could amplify the impacts of collateral constraints in a similar way.

Our paper mainly contributes to the misallocation literature.² Several papers have also documented that endogenizing firm TFP or allowing for productivity-enhancing inputs amplifies aggregate productivity loss arising from policy distortions (e.g., Gabler and Poschke 2013; Bhattacharya, Guner, and Ventura 2013; Ranasinghe 2014; Da-Rocha, Restuccia, and Tavares 2023) and more specifically from collateral constraints (e.g., Lopez-Martin 2017; Vereshchagina 2023). We differ from these papers by highlighting that in addition to effects on aggregate productivity, allowing for nonhomothetic managerial inputs allows us to better match the persistence in MRPK dispersion among firm cohorts and to explain how large and productive firms may be constrained as well. We also highlight theoretically that the key to these results is that large firms spend disproportionately more on managerial inputs, a pattern consistent with data. In this way, our paper is also related to the recent macroeconomic literature on the firm size distribution, firm management, and their relationship to economic development.³ Finally, our paper studies frictions in the Chinese context and hence is also related to the literature on misallocation in China.⁴

²See Restuccia and Rogerson (2008); Guner, Ventura, and Xu (2008); Hsieh and Klenow (2009); Buera and Shin (2013); Moll (2014); Midrigan and Xu (2014); Adamopoulos and Restuccia (2014); Hsieh et al. (2019); and Chen, Restuccia, and Santaella-Llopis (2023), among others.

³See Garicano and Rossi-Hansberg (2006); Bloom and Van Reenen (2010); Haltiwanger, Jarmin, and Miranda (2013); Hsieh and Klenow (2014); Grobovšek (2020); and Acigit, Alp, and Peters (2021), among others.

⁴See Brandt, Tombe, and Zhu (2013); Hsieh and Song (2015); Bai, Lu, and Tian (2018); Tombe and Zhu (2019); Gai et al. (2021); König et al. (2022); Adamopoulos, Brandt, Chen, et al. (2022); and Adamopoulos, Brandt, Leight, et al. (2022), among others.

I. Evidence on Firm Size and Managerial Inputs

Literature has provided evidence that managerial inputs are nonhomothetic in firm size. Akcigit, Alp, and Peters (2021) use firm-level data from the United States and document that firms with more than 100 employees have higher than 10 percent managerial employment shares on average, while firms with fewer than five employees have virtually no managers. Similarly, Grobovšek (2020) studies French firm-level data and documents two important facts. First, the share of managerial employees increases with firm size. Second, the share of managerial compensation is higher for larger firms and hence the profit share declines with firm size.

We also observe this nonhomotheticity of managerial inputs by firm size in the Chinese firm-level data, the Annual Surveys of Industrial Production for the period of 1998–2007 (National Bureau of Statistics of China 2007). The data include information on firms' capital, labor, intermediate input, and output. Additionally, the 2004 sample also includes information on worker composition.⁵ We define managers as workers with senior titles but who are not technicians, sort firms by size (number of employees), and then calculate the percentage of employees working as managers in each size group as the total head count of managers divided by the total head count of employees. The results are in Table 1. Among all firms, around 4.1 percent of workers are managers. This number is clearly increasing in firm size: for instance, among the largest 5 percent of firms, this number is 4.9 percent, which is significantly higher than that of the entire sample (4.1 percent). It further increases to 5.8 percent among the largest 1 percent of firms, and it is significantly different from that of the largest 5 percent of firms.⁶ Clearly, larger firms hire disproportionately more managers compared to smaller firms.⁷

Motivated by the evidence, we next introduce nonhomothetic managerial inputs into an otherwise standard collateral constraint model and reexamine the role of financial frictions in capital misallocation.

II. Model

A. Preferences and Endowments

The economy consists of two types of infinitely lived individuals: workers and entrepreneurs. There is a measure N_w of infinitely lived workers. In each period, each worker has one unit of time that is supplied inelastically to the labor market and earns a flat wage income. Workers' labor supply is used as production labor or transformed to managerial inputs. Workers do not save and live hand to mouth. In addition, there is a measure N_e of infinitely lived entrepreneurs, who differ in exogenous entrepreneurial

⁵Online Appendix A provides a detailed description of data.

⁶Note that the elasticity of manager share with respect to firm size is smaller than those found in Grobovšek (2020) and Akcigit, Alp, and Peters (2021), who use French and US data. This is likely because of more severe contracting frictions in China between entrepreneurs and managers, which hinder productive firms from hiring outside managers and expanding, as discussed in Grobovšek (2020) and Akcigit, Alp, and Peters (2021).

⁷While our focus in this paper is on managerial inputs, the nonhomotheticity also applies more generally to skilled labor inputs. For instance, 8.3 percent of employees have some college education in our sample. If we restrict to the largest five percent of firms, this number increases to 9.6 percent and further increases to 10.7 percent among the largest 1 percent of firms. Details are in Table 1 in online Appendix B.

TABLE 1—MANAGER-WORKER RATIO AMONG FIRMS OF DIFFERENT SIZE

	Employment threshold	Managers as percentage of total employees
All firms	–	4.1 (0.1)
Largest 25% of firms	200	4.2 (0.1)
Largest 10% of firms	435	4.5 (0.2)
Largest 5% of firms	733	4.9 (0.3)
Largest 1% of firms	2,200	5.8 (0.8)

Notes: This table lists the percentage of total employees working as managers across different sizes of firms. For each group, we separately calculate the total head count of managers and divide it by the total head count of employees to obtain our percentage. Standard errors obtained from bootstrap repetitions are in parentheses.

Source: Annual Surveys of Industrial Production from the National Bureau of Statistics of China

ability z . Entrepreneurs operate firms to produce the single output good, which is treated as the numeraire and can be used for consumption or capital formation. Note that we abstract from the occupational choice problem between entrepreneurs and workers to focus on the misallocation among incumbent firms rather than selection.

Entrepreneurs’ preferences are described by the following utility function:

$$U(\mathbf{c}) = \mathbb{E}_z \left[\sum_{t=0}^{\infty} \beta^t u(c_t) \right], \quad \text{where} \quad u(c_t) = \frac{c_t^{1-\sigma} - 1}{1 - \sigma}.$$

Here, β is the discount factor and σ is the coefficient of relative risk aversion. The expectation is taken over the realization of ability z , which varies over time according to a stochastic process known to entrepreneurs. Worker preferences are similar except that they are not subject to the uncertainty arising from entrepreneurial ability.

B. The Entrepreneur’s Problem

An entrepreneur with ability z can operate a firm with endogenous productivity $A(z, m)$. Here, m is the number of hired managers. We assume that $A(z, m)$ is increasing in z and m . The production function is

$$y = A(z, m)^{1-\gamma} (k^\alpha n^{1-\alpha})^\gamma,$$

where k and n are capital and production labor input, respectively, and α and γ determine the factor shares and the span of control.

We follow Evans and Jovanovic (1989) and Moll (2014) by assuming that the collateral constraint takes the form of $k \leq \phi a$. Here, a is the entrepreneur’s asset holdings used as collateral and parameter ϕ hence governs the stringency of the collateral constraint, where a smaller ϕ indicates a tighter constraint. This parameter can be easily microfounded by the degree of contract enforcement in an economy, as in Buera, Kaboski, and Shin (2011) and Midrigan and Xu (2014).

The firm, operated by an entrepreneur with ability z and asset holdings a , has the following profit maximization problem:

$$(1) \quad \pi(a, z) = \max_{m, k, n} \left\{ A(z, m)^{1-\gamma} (k^\alpha n^{1-\alpha})^\gamma - Rk - wn - p_m m \right\},$$

subject to

$$k \leq \phi a,$$

where R and w are the interest rate and wage rate, respectively, and p_m is the unit cost of managerial service. Denote the demand for capital, labor, and managerial input as $k^d(a, z)$, $n^d(a, z)$, and $m^d(a, z)$, respectively, and the output as $y(a, z)$.

An entrepreneur begins a period with asset holdings a and ability z . Her consumption-savings problem can be written in recursive form:

$$V(a, z) = \max_{a' \geq 0} \left\{ \frac{c^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_{z'} [V(a', z') | z] \right\},$$

subject to

$$c + a' \leq (1 + r)a + \pi(a, z),$$

where we use x' to denote the value of x in the next period.

C. Market Arrangement

A representative financial intermediary owns capital and rents it to entrepreneurs at interest rate R . This financial intermediary finances its capital through issuing a one-period risk-free bond (a) that is held by entrepreneurs, which is in turn used as their collateral. The interest rate of this bond is r . The financial intermediary makes zero profit and hence we have $R = r + \delta$ in equilibrium, where δ is the depreciation rate of capital.

It costs κ units of labor to produce a manager, where $\kappa > 1$ represents for instance costs for training managers. The unit cost of m is hence $p_m = w\kappa$. As such, aggregate labor demand consists of two components: production labor and labor used to train managers.

D. Aggregation and Equilibrium

Let $G(a, z)$ be the joint distribution of entrepreneurs over the asset holdings and ability. Aggregate demand for managers m is given by

$$M^d = N_e \int_{a, z} m^d(a, z) G(da, dz),$$

where $m^d(a, z)$ represents the demand for managers of a firm with asset (bond) holdings a and entrepreneurial productivity z . To produce M^d managers, $M^d \kappa$ units of labor are used. Aggregate capital, labor, and output demands are hence given by

$$\begin{aligned} K^d &= N_e \int_{a,z} k^d(a, z) G(da, dz), \\ N^d &= N_e \int_{a,z} n^d(a, z) G(da, dz) + M^d \kappa, \text{ and} \\ Y^d &= \delta K^d + N_e \int_{a,z} c(a, z) G(da, dz) + N_w c_w, \end{aligned}$$

where $c(a, z)$ is the consumption of entrepreneurs of type (a, z) and c_w is worker consumption. Aggregate capital, labor, and output supplies are

$$\begin{aligned} K^s &= N_e \int_{a,z} a G(da, dz), \\ N^s &= N_w, \text{ and} \\ Y^s &= N_e \int_{a,z} y(a, z) G(da, dz). \end{aligned}$$

The formal definition of the stationary competitive equilibrium is in online Appendix C.

E. Nonhomothetic Productivity and Financial Constraints

Before moving on to quantitative exercises, we first discuss a key property of our model, nonhomotheticity of managerial inputs, and how it interacts with firms' financial constraints.

The firm optimization problem, (1), can be written in two steps. First, given the capital stock, the firm chooses the number of managers m and labor input n to maximize the operating profit:

$$(2) \quad \tilde{\pi}(z, k) = \max_{m,n} \left\{ A(z, m)^{1-\gamma} (k^\alpha n^{1-\alpha})^\gamma - wn - p_m m \right\}.$$

Then (1) can be rewritten as

$$\pi(a, z) = \max_k \left\{ \tilde{\pi}(z, k) - Rk \right\},$$

subject to

$$k \leq \phi a.$$

The first-order conditions of the first step of the optimization problem, (2), are

$$\begin{aligned} \gamma(1 - \alpha)A(z, m)^{1-\gamma} k^{\alpha\gamma} n^{(1-\alpha)\gamma-1} &= w, \\ (1 - \gamma)A(z, m)^{-\gamma} \frac{\partial A(z, m)}{\partial m} k^{\alpha\gamma} n^{(1-\alpha)\gamma} &= p_m. \end{aligned}$$

It can be easily shown that the optimal m and n are both increasing in k . Let

$$\varepsilon_{A,m} = \frac{\partial \ln A(z, m)}{\partial \ln m}$$

be the elasticity of productivity $A(z, m)$ with respect to the number of managers m . Then, from the first-order conditions above, we have

$$(3) \quad \frac{m}{n} = \frac{w}{p_m} \frac{1 - \gamma}{\gamma} \frac{1}{1 - \alpha} \varepsilon_{A,m}.$$

That is, the optimal ratio of managers to production workers of a firm is proportional to the elasticity $\varepsilon_{A,m}$. As we documented in Section I, this ratio is increasing with firm size and hence the number of managers m in the data. To be consistent with the empirical fact, we make the following assumption about the productivity function:

ASSUMPTION 1: *The productivity function $A(z, m)$ is such that $\varepsilon_{A,m}$ increases in m .*

This empirically motivated assumption has three important implications. First, it implies that the productivity function is nonhomothetic with respect to the number of managers. Second, it implies that the share of operating profit is decreasing in firm size, which can be seen clearly from the following equation:

$$\frac{\tilde{\pi}(z, k)}{y(z, k)} = 1 - \gamma(1 - \alpha) - (1 - \gamma)\varepsilon_{A,m}.$$

Thus, as an entrepreneur accumulates assets, capital $k = \lambda a$ increases, m increases, and then the profit margin decreases, consistent with evidence in Grobovšek (2020). As a result, as a firm grows, the entrepreneur's ability to accumulate assets does not increase proportionately due to lower profit margin earned by the entrepreneur.

Finally, this assumption implies that a firm's elasticity of scale also increases with firm size. Specifically, the elasticity of scale, which characterizes what happens to output if we scale up all input by some small amount ψ , is given by

$$\begin{aligned} e(m, k, n) &= \left. \frac{d \ln y(\psi m, \psi k, \psi n)}{d \ln \psi} \right|_{\psi=1} = (1 - \gamma) \left. \frac{d \ln A(z, \psi m)}{d \ln \psi} \right|_{\psi=1} + \gamma \\ &= (1 - \gamma)\varepsilon_{A,m} + \gamma. \end{aligned}$$

If $\varepsilon_{A,m} \in (0, 1)$ and $\varepsilon_{A,m}$ increases in m , then the technology has decreasing returns to scale, but the elasticity of scale increases in m and hence in firm size. This property that hiring managers helps increase the elasticity of scale is consistent with evidence in Grobovšek (2020) and Akcigit, Alp, and Peters (2021), and our framework can be viewed as a reduced-form approach of the hierarchy models such as Garicano and Rossi-Hansberg (2006) and Grobovšek (2020).

The increasing elasticity of scale tends to partially offset the self-financing mechanism. As an entrepreneur with binding collateral constraint accumulates assets, she is able to borrow more; k increases and hence the MRPK declines, which is the standard self-financing mechanism. In our model, however, as k increases, the optimal m increases. With increasing $\varepsilon_{A,m}$, the elasticity of scale increases, which in turn increases capital demand and raises the MRPK. This mechanism partially undoes the standard self-financing mechanism. As a result, firm MRPK declines more slowly along with self-finance, making the MRPK dispersion among firm cohorts more persistent.

In summary, in our model with a productivity function that is nonhomothetic in managerial inputs, as a firm accumulates collateral and physical capital, its profit margin declines, which slows down asset accumulation, and its elasticity of scale increases, which reduces the negative effect of asset accumulation on MRPK. Both of these effects lengthen the time when the firm faces financial constraints. These effects would be absent, however, if the technology does not allow for managerial inputs or if the productivity elasticity with respect to the number of managers is constant.

III. Quantitative Results

We now quantify the role of financial constraints in our model that is calibrated to Chinese data. In particular, we compare the predictions of our model to that of an otherwise identical model without managerial inputs, which is similar to Buera, Kaboski, and Shin (2011) or Midrigan and Xu (2014) without firm entry and exit. We also use our quantitative results to further highlight the importance of nonhomothetic productivity function with respect to managerial inputs.

A. Calibration

Given that our goal is to compare the quantitative predictions of two models—with and without nonhomothetic managerial inputs—it is crucial that we calibrate them to match the same set of data moments. Equally important is that we target a set of moments that are typically chosen in the literature to help the comparison. We calculate the data moments using information from the Annual Surveys of Industrial Production (National Bureau of Statistics of China 2007) and the 1 percent National Population Sample Survey in 2005 (National Bureau of Statistics of China 2005). Note that matching the same set of moments does not imply the same parameter values between the two models.

Parameterization.—For our quantitative analysis, we assume the functional form of firm productivity to be

$$A(z, m) = e^z \left(T^{\frac{\theta-1}{\theta}} + \lambda m^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta\eta}{\theta-1}},$$

where T is the entrepreneur's own time spent in management, which we normalize to unity without loss of generality; m is the measure of hired professional managers;

$\lambda < 1$ governs the contribution of the outside managers to firm productivity; $\theta > 1$ governs the elasticity of substitution between the entrepreneur's own time and that of outside managers; and η determines the maximum elasticity of scale. Our setup nests Akcigit, Alp, and Peters (2021) as a special case when we set θ to infinity and $\eta = 1$. λ can be interpreted as supervision efficiency, given that the entrepreneur needs to expend effort to supervise the outside managers, with a lower λ indicating a lower supervision efficiency (Akcigit, Alp, and Peters 2021). One can verify that

$$\varepsilon_{A,m} = \eta \frac{\lambda m^{\frac{\theta-1}{\theta}}}{T^{\frac{\theta-1}{\theta}} + \lambda m^{\frac{\theta-1}{\theta}}}$$

and hence it is increasing in m as long as $\theta > 1$. Note that $\varepsilon_{A,m} \leq \eta$ and hence the maximum elasticity of scale is $\gamma + (1 - \gamma)\eta$.

We follow Midrigan and Xu (2014) in assuming that entrepreneurial ability z has a permanent component \bar{z} and a transitory component \tilde{z} : $z = \bar{z} + \tilde{z}$. The permanent component \bar{z} follows a Gaussian distribution with standard deviation $\sigma_{\bar{z}}$. The transitory component \tilde{z} follows an AR(1) process with Gaussian disturbances:

$$\tilde{z}' = (1 - \rho)\tilde{z} + \varepsilon_{\tilde{z}},$$

where ρ determines the persistence of the transitory component and $\varepsilon_{\tilde{z}}$ is the disturbance term with a standard deviation $\sigma_{\tilde{z}}$. This AR(1) process is then approximated using the Rouwenhorst method in our quantitative analysis.

Determining Parameter Values.—We now briefly describe how we determine the value of parameters.

Demographics and Preferences: N_w and N_e govern the population share of workers and entrepreneurs. We normalize $N_e = 1$ and choose $N_w = 5.43$ such that 15.5 percent of individuals are entrepreneurs, as in the 2005 Chinese population census. We choose the coefficient of relative risk aversion σ to be 2. The discount factor β is chosen in both models to match an overall capital-to-output ratio of 3 as we observed in the Penn World Table (Feenstra, Inklaar, and Timmer 2015).⁸

Entrepreneurial Ability Distribution: We follow Midrigan and Xu (2014) and choose the persistence parameter ρ and dispersion parameters $\sigma_{\bar{z}}$ and $\sigma_{\tilde{z}}$ to jointly match three moments from the data: the one-year and five-year autocorrelation of log output of 0.88 and 0.77, respectively, and the standard deviation of log output of 1.26.

⁸The capital-to-output ratio for China varies substantially in different versions of the Penn World Table. For the year 2004, the capital-output ratio is around 3.40 in version 9.1 (Feenstra, Inklaar, and Timmer 2019) and 2.53 in version 10.0 (Feenstra, Inklaar, and Timmer 2021). We hence choose a value of 3, which falls roughly in the middle.

Technologies: The elasticity of capital input α is chosen to match capital share of 0.33.⁹ In our benchmark model, γ is not the typical span-of-control parameter since the managerial input enters $A(z, m)$. Because the span of control is closely related to the profit margin, we choose γ such that the aggregate profit margin is identical between the two models at 0.3, which is crucial in comparison (Vereshchagina 2023).¹⁰ The rate of depreciation δ is set to 0.06.

Collateral Constraint: We follow the common practice in the literature of choosing ϕ to match the debt-to-output ratio in the Chinese data of 0.64.

Management: The management parameters only apply to our benchmark model with nonhomothetic managerial inputs. Recall that each unit of managerial inputs is produced with κ units of labor. We choose $\kappa = 1.96$ such that the wage premium of managers relative to workers is 1.96, as in the 2005 Chinese population census. We choose $\eta = 0.63$ such that the elasticity of scale is bounded from above by $\gamma + (1 - \gamma)\eta = 0.9$ or the largest firm in the limit has a profit share of 10 percent. The efficiency of supervision λ and the elasticity between the entrepreneur's own time and that of managers θ are chosen to jointly match two moments: (i) in aggregate, 4.1 percent of the worker population works as managers and (ii) the manager-to-worker ratio of the largest 1 percent of firms is 19.9 percent higher than that of the largest 5 percent of firms. The second moment exploits the key prediction of our model that m/n increases in firm size.

In summary, we have 15 parameters (11 for the model without managers) in total, with N_e , N_w , σ , κ , and δ taking directly assigned values and η , γ , β , ρ , $\sigma_{\bar{z}}$, $\sigma_{\bar{z}}$, α , ϕ , λ , and θ being jointly determined by comparing equilibrium model moments with those from the data. The values of these parameters are listed in Table 2.

A key implication of our model is that the operating profit share of value added declines with firm size. Using the Chinese firm-level panel data, we regress the operating profit share on firm size measured by log employment, controlling for firm fixed effects. We find a significantly negative coefficient on firm size of -0.0142 , implying that a 100 percent increase in firm size is related to a 1.42 percentage point decline in the operating profit share. Using the simulated data from our model, we find that a 100 percent increase in firm size reduces the operating profit share by 0.72 percentage points. Hence, our model accounts for a large portion of the decline in the operating profit share with firm growth observed in the data.

B. Model Comparison

We now compare the quantitative predictions of our benchmark model with nonhomothetic managerial inputs to those of the model without managers, both of which are calibrated to match the same sets of moments.

⁹Note that with collateral constraints, a capital share of 0.33 does not necessarily imply that $\alpha\gamma = 0.33$ since MRPK does not necessarily equal the interest rate in our case.

¹⁰The targeted profit margin varies in the literature. For instance, Restuccia and Rogerson (2008) and Midrigan and Xu (2014) choose 0.15, while Yang (2021) chooses 0.5. Our choice of 0.3 falls in the ballpark. Note that a lower profit margin and hence a higher γ implies larger misallocation (Hopenhayn 2014).

TABLE 2—CALIBRATION: PARAMETERS AND VALUES

Parameters	Value		
	Benchmark	Without managers	Data moments
N_e : measure of entrepreneurs	1	1	Normalization
N_w : measure of workers	5.433	5.433	Entrepreneur share of 15.5%
σ : coefficient of relative risk aversion	2	2	Literature
β : discount factor	0.928	0.932	Capital-output ratio of 3
ρ : autocorrelation of ability	0.489	0.486	1-year autocorrelation of output of 0.88
$\sigma_{\bar{z}}$: SD of permanent component	1.004	1.095	5-year autocorrelation of output of 0.77
$\sigma_{\tilde{z}}$: SD of i.i.d. disturbance	0.663	0.679	SD of log output of 1.26
γ : span of control	0.727	0.744	Identical profit share (0.3) between models
α : elasticity of capital ($\alpha\gamma$)	0.532	0.502	Capital share of 0.33
δ : depreciation rate	0.06	0.06	Literature
ϕ : collateral constraint	1.474	1.522	Debt-output ratio of 0.64
κ : labor used to produce management	1.960	–	Manager wage premium of 1.96
η : return to management	0.634	–	Highest return to scale of 0.9
λ : efficiency of supervision	0.256	–	4.1% of workers work as managers
θ : elasticity: entrepreneur and managers	1.675	–	Distribution of manager-worker ratio
Untargeted moment	Benchmark	Without managers	Data
Semielasticity of operating profit share with respect to size	–0.0072	0	–0.0142

Notes: This table lists the calibrated parameter values and the model-implied elasticity of the operating profit share with respect to firm size in both our benchmark model and the model without managerial inputs, respectively, along with the corresponding data moments.

We begin by showing how allowing for nonhomothetic managerial inputs quantitatively increases the persistence of collateral constraints for productive entrepreneurs. Consider in each model a peak-ability entrepreneur (with ability \bar{z} and \tilde{z} at the highest grid point) who has little collateral (with assets a at the twenty-fifth percentile of the stationary distribution) and for whom the collateral constraint initially binds in both models. In the model without managers, this entrepreneur, following her optimal policy function, undoes the collateral constraint in about 19 periods. In contrast, it takes the same entrepreneur 35 periods to self-finance in our benchmark model, a significant increase in persistence.

Our model with nonhomothetic managerial inputs also increases the persistence of MRPK dispersion of firm cohorts, improving the model's ability to match this feature of the data documented in, for instance, David and Venkateswaran (2019). Consider a firm cohort consisting of the peak-ability entrepreneurs who have initial assets matching the equilibrium invariant marginal distribution for their type, $G(a, z | \bar{z} = \bar{z}^{max}, \tilde{z} = \tilde{z}^{max})$.¹¹ The collateral constraint is initially binding for most of them. We use their policy functions to calculate the evolution of their assets and to trace out the dispersion of MRPK within this cohort over time, keeping their ability invariant. The results are reported in the first four rows of Table 3. In the model without managers, the standard deviation of log MRPK falls to less than 10 percent of its initial level by the fifteenth period. In our benchmark model, however, the standard

¹¹Note that without entry or exit, firm age is not well defined in our model. We hence focus on a firm cohort constructed with assets matching its distribution in the stationary equilibrium.

TABLE 3—COMPARISON BETWEEN TWO SETUPS

	Benchmark model	Model without managers
<i>Panel A. Dispersion in MRPK of a constructed cohort (percent)</i>		
Initial (normalized)	100	100
14th period	30.8	11.3
15th period	29.3	2.0
28th period	11.6	0.0
29th period	7.6	0.0
<i>Panel B. Percent of firms with binding financial constraint, by firm size</i>		
Q1	30.9	24.2
Q2	42.3	35.3
Q3	47.3	43.1
Q4	59.3	52.2
<i>Panel C. Changes after eliminating financial constraint (percent)</i>		
Aggregate output	+6.4	+3.7
Firm capital usage, by productivity quartiles		
Q1	−30.0	−24.7
Q2	−26.9	−21.0
Q3	−13.4	−15.2
Q4	+21.6	+16.7

Notes: This table compares moments of interest computed at the stationary equilibrium for our benchmark model and the model without managerial inputs, both of which are calibrated to match the same data moments. MRPK dispersion is computed from a firm cohort consisting of entrepreneurs with ability z at the highest grid point and initial assets matching the equilibrium marginal distribution for their type, $G(a, z | \bar{z} = \bar{z}^{max}, \bar{z} = \bar{z}^{max})$.

deviation falls to less than 10 percent of its initial level by the twenty-ninth period, which almost doubles the length of the model without managers.

Due to greater persistence in the collateral constraint, firms of all sizes are more likely to be financially constrained in our benchmark model than in the model without managerial inputs, as shown in the middle four rows of Table 3. After eliminating the collateral constraint, there is also more capital reallocation in our benchmark model than in the model without managers. The last four rows of Table 3 show that the amount of capital used by the top TFP quartile firms increases by 21.6 percent in the benchmark model but only 16.7 percent in the model without managers. Consequently, allowing for nonhomothetic managerial inputs substantially amplifies the effect of collateral constraints on aggregate TFP. Eliminating collateral constraints in the benchmark model increases aggregate TFP by 6.4 percent, in contrast to only 3.7 percent in the model without managerial inputs.

The larger aggregate TFP loss in our benchmark model are not driven by channels previously identified as important in the literature: higher equilibrium firm TFP dispersion or lower firm TFP persistence. First, the standard deviation of log of firm TFP $A(z, m)$ is similar between the two models (1.333 in the benchmark model and 1.336 in the model without managerial inputs), as we calibrate the ability distribution in both to match the same data moment, dispersion in firm output. Second, while the literature shows that less persistent ability processes increase TFP losses (e.g., Moll 2014), this is not the driving reason in our case, as the calibrated values of ρ and the relative importance of \bar{z} and \bar{z} are similar between the two models. Nevertheless, we conduct a robustness exercise in online Appendix D by recalibrating the model without managerial inputs that restricts the ability process z to be identical to that of our benchmark model, while the remaining

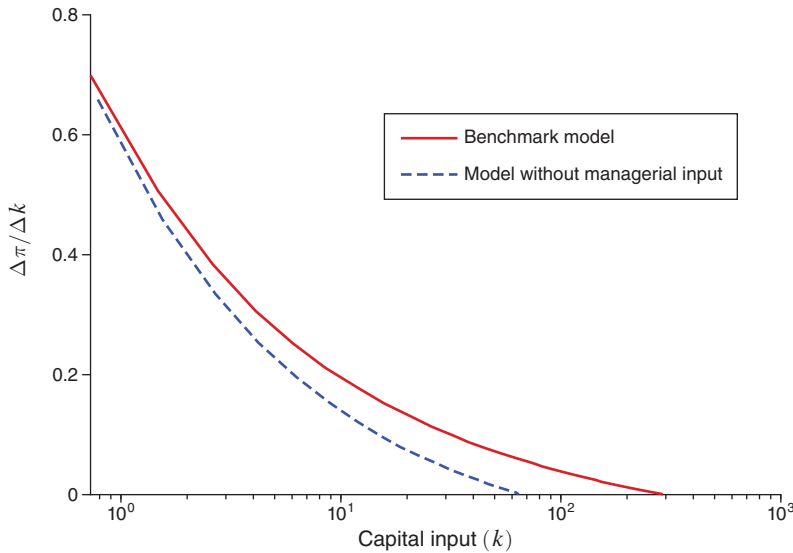


FIGURE 1. RETURN TO CAPITAL

Notes: This figure illustrates the return to capital, calculated as $\Delta\pi/\Delta k$, for the peak-ability entrepreneur (with ability \bar{z} and \tilde{z} at the highest grid point) for different levels of k for the benchmark model and the model without managerial inputs, respectively.

parameters are calibrated to match the same moments, and all predictions remain similar. More generally, online Appendix D shows that our results hold even if we restrict the value of all parameters, except for the managerial ones, to be the same in both models. Hence, we conclude that our results are not driven by parameter value differences. Finally, the equilibrium dispersion in MRPK is slightly larger in the benchmark model than the model without managerial inputs. Our results hold if we recalibrate the model without managerial inputs to match the same MRPK dispersion rather than the debt-to-output ratio.

C. Discussion

Understanding the Mechanisms.—To further illustrate how the mechanism of increasing the elasticity of scale matters, we plot in Figure 1 the return to capital, calculated as $\Delta\pi/\Delta k$, for the peak-ability entrepreneur for different levels of k , for both models. Note that we normalize capital employed by this entrepreneur by average capital per entrepreneur in each model to make sure it is unit free. One can clearly see that for all level of capital k , the return of additional capital is higher in the benchmark model than in the model without managerial inputs, highlighting the property that allowing for managerial inputs increases capital demand through increasing the elasticity of scale.

We present a decomposition exercise to illustrate the importance of the two mechanisms at play in our benchmark model—lower profit margins and increasing elasticity of scale. Specifically, we design a type-specific tax/subsidy to entrepreneurs, $\tau(a, z)$, such that the operating profit share, $\tilde{\pi}/y$, is constant, and this

tax/subsidy is revenue neutral ($\int_{a,z} \tau(a,z) G(da, dz) = 0$), not involving any aggregate transfer between workers and entrepreneurs (Itskhoki and Moll 2019). This tax affects the entrepreneur's consumption-savings decision by equalizing the operating profit share and hence shuts off the varying profit margin mechanism but does not affect the firm's profit maximization problem and the mechanism of varying the elasticity of scale. With this tax, it takes 23 periods to eliminate 90 percent of MRPK dispersion following an entrepreneur cohort with the highest grid point ability and the equilibrium distribution of assets a , 6 periods shorter than in the benchmark model but 8 periods longer than in the model without managerial inputs. Hence, both mechanisms contribute to greater persistence of MRPK dispersion.

Note that our calibration strategy implies that the average profit margin, and hence the average elasticity of scale, is identical between the two models. In our benchmark model, however, the profit share and the elasticity are heterogeneous. Specifically, low-ability entrepreneurs have smaller firms with higher operating profit share and lower elasticity of scale and hence self-finance faster than their counterparts in the model without managerial inputs; on the contrary, high-ability entrepreneurs have larger firms with lower operating profit share and higher elasticity of scale and hence self-finance slower. In the stationary equilibrium, high-ability entrepreneurs are more likely to have binding collateral constraints; therefore, on average it takes longer for entrepreneurs in our benchmark model to accumulate enough assets to become unconstrained.

The Importance of Varying $\varepsilon_{A,m}$.—The assumption that $\varepsilon_{A,m}$ increases in m is key to our results. To see this, we consider an otherwise identical model with managerial inputs but we set $\theta = 1$ such that the elasticity of $A(z, m)$ with respect to m is constant. In this case, the production function is simply

$$y = (e^z)^{1-\gamma} \Omega m^{\frac{\lambda\eta(1-\gamma)}{1+\lambda}} (k^\alpha n^{1-\alpha})^\gamma,$$

where Ω is a collection of constants. Clearly, in this case, the manager-to-worker ratio m/n should be identical across firms. One can then redefine a composite labor input as

$$\tilde{n} = \left(m^{\frac{\lambda\eta(1-\gamma)}{1+\lambda}} n^{(1-\alpha)\gamma} \right)^{\frac{1}{(1-\alpha)\gamma}},$$

and then the production function can be written as

$$y = (e^z)^{1-\gamma} (k^\alpha \tilde{n}^{1-\alpha})^\gamma.$$

With a calibration strategy that targets the same profit share and capital/labor share, this production function is identical to the one in the model without managerial inputs and hence in this case allowing for managerial inputs does not directly affect the role of the collateral constraints. Intuitively, when m/n is identical across firms, by allowing for managerial inputs, we implicitly split the elasticity of labor into two components—that of raw labor and that of managers. This should not directly affect misallocation as long as there is no distortion between m and n .

IV. Conclusion

The canonical model of collateral constraints typically predicts that they bind only for young firms and small firms, while older firms are unaffected due to their accumulated assets. This self-financing channel also leads these models to generate dispersion in MRPK that declines too rapidly within a firm cohort compared to the data. We argue that allowing firms to hire professional managers moves the predictions of models with collateral constraints closer to the data by partly offsetting the effects of the self-financing channel. Particularly, along with self-finance, firms grow larger and optimally spend disproportionately more on managerial inputs, reducing their profit margin and ability to self finance; in addition, hiring more managers helps increase the elasticity of scale, thus further increasing capital demand.

We then calibrate our model to Chinese data. By comparing our benchmark model to a similarly calibrated model without managerial inputs, we find that in our benchmark model, it takes twice as long for an entrepreneur with high productivity but low net worth to accumulate enough assets to become unconstrained, and the dispersion of MRPK within a firm cohort is also substantially more persistent. These properties imply that with nonhomothetic managerial inputs, high-productivity firms are more likely to be constrained and, as a result, the impact of collateral constraints on aggregate output is twice as large.

Although we interpret the productivity-enhancing input in our model as management practices, our findings are potentially more general. Other productivity-enhancing inputs, such as skilled labor or innovation efforts, could have similar effects provided that larger firms spend disproportionately more on these inputs.

REFERENCES

- Adamopoulos, Tasso, Loren Brandt, Chaoran Chen, Diego Restuccia, and Xiaoyun Wei. 2022. "Land Security and Mobility Frictions." NBER Working Paper 29666.
- Adamopoulos, Tasso, Loren Brandt, Jessica Leight, and Diego Restuccia. 2022. "Misallocation, Selection, and Productivity: A Quantitative Analysis with Panel Data from China." *Econometrica* 90 (3): 1261–82.
- Akcigit, Ufuk, Harun Alp, and Michael Peters. 2021. "Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries." *American Economic Review* 111 (1): 231–75.
- Bai, Yan, Dan Lu, and Xu Tian. 2018. "Do Financial Frictions Explain Chinese Firms' Saving and Misallocation?" NBER Working Paper 24436.
- Banerjee, Abhijit V., and Benjamin Moll. 2010. "Why Does Misallocation Persist?" *American Economic Journal: Macroeconomics* 2 (1): 189–206.
- Bhattacharya, Dhritiman, Nezh Guner, and Gustavo Ventura. 2013. "Distortions, Endogenous Managerial Skills and Productivity Differences." *Review of Economic Dynamics* 16 (1): 11–25.
- Bloom, Nicholas, and John Van Reenen. 2007. "Measuring and Explaining Management Practices across Firms and Countries." *Quarterly Journal of Economics* 122 (4): 1351–408.
- Bloom, Nicholas, and John Van Reenen. 2010. "Why Do Management Practices Differ across Firms and Countries?" *Journal of Economic Perspectives* 24 (1): 203–24.
- Brandt, Loren, Trevor Tombe, and Xiaodong Zhu. 2013. "Factor Market Distortions across Time, Space and Sectors in China." *Review of Economic Dynamics* 16 (1): 39–58.
- Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin. 2011. "Finance and Development: A Tale of Two Sectors." *American Economic Review* 101 (5): 1964–2002.
- Caselli, Francesco. 2005. "Accounting for Cross-Country Income Differences." In *Handbook of Economic Growth*, Vol. 1A, edited by Philippe Aghion and Steven N. Durlauf, 679–741. Amsterdam: North-Holland.

- Chen, Chaoran, Ashique Habib, and Xiaodong Zhu.** 2023. "Replication data for: Finance, Managerial Inputs, and Misallocation." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. <https://doi.org/10.3886/E183144V1>.
- Chen, Chaoran, Diego Restuccia, and Raül Santaella-Llopis.** 2023. "Land Misallocation and Productivity." *American Economic Journal: Macroeconomics* 15 (2): 441–65.
- Da-Rocha, José-María, Diego Restuccia, and Marina M. Tavares.** 2023. "Policy Distortions and Aggregate Productivity with Endogenous Establishment-Level Productivity." *European Economic Review* 155: 104444.
- David, Joel M., and Venky Venkateswaran.** 2019. "The Sources of Capital Misallocation." *American Economic Review* 109 (7): 2531–67.
- Evans, David S., and Boyan Jovanovic.** 1989. "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints." *Journal of Political Economy* 97 (4): 808–27.
- Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer.** 2015. "The Next Generation of the Penn World Table." *American Economic Review* 105 (10): 3150–82.
- Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer.** 2019. "Penn World Table 9.1." Groningen Growth and Development Centre. <https://doi.org/10.15141/S50T0R> (accessed September 19, 2022).
- Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer.** 2021. "Penn World Table 10.0." Groningen Growth and Development Centre. <https://doi.org/10.15141/S5Q94M> (accessed September 19, 2022).
- Gabler, Alain, and Markus Poschke.** 2013. "Experimentation by Firms, Distortions, and Aggregate Productivity." *Review of Economic Dynamics* 16 (1): 26–38.
- Gai, Qingen, Naijia Guo, Bingjing Li, Qinghua Shi, and Xiaodong Zhu.** 2021. "Migration Costs, Sorting, and the Agricultural Productivity Gap." University of Toronto Department of Economics Working Paper 693.
- Garicano, Luis, and Esteban Rossi-Hansberg.** 2006. "Organization and Inequality in a Knowledge Economy." *Quarterly Journal of Economics* 121 (4): 1383–435.
- Grobovšek, Jan.** 2020. "Managerial Delegation, Law Enforcement, and Aggregate Productivity." *Review of Economic Studies* 87 (5): 2256–89.
- Guner, Nezih, Andrii Parkhomenko, and Gustavo Ventura.** 2018. "Managers and Productivity Differences." *Review of Economic Dynamics* 29: 256–82.
- Guner, Nezih, Gustavo Ventura, and Yi Xu.** 2008. "Macroeconomic Implications of Size-Dependent Policies." *Review of Economic Dynamics* 11 (4): 721–44.
- Haltiwanger, John, Ron S. Jarmin, and Javier Miranda.** 2013. "Who Creates Jobs? Small versus Large versus Young." *Review of Economics and Statistics* 95 (2): 347–61.
- Hopenhayn, Hugo A.** 2014. "Firms, Misallocation, and Aggregate Productivity: A Review." *Annual Review of Economics* 6: 735–70.
- Hsieh, Chang-Tai, and Peter J. Klenow.** 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics* 124 (4): 1403–48.
- Hsieh, Chang-Tai, and Peter J. Klenow.** 2014. "The Life Cycle of Plants in India and Mexico." *Quarterly Journal of Economics* 129 (3): 1035–84.
- Hsieh, Chang-Tai, and Zheng (Michael) Song.** 2015. "Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China." *Brookings Papers on Economic Activity* 46 (1): 295–346.
- Itskhoki, Oleg, and Benjamin Moll.** 2019. "Optimal Development Policies with Financial Frictions." *Econometrica* 87 (1): 139–73.
- Klenow, Peter J., and Andrés Rodríguez-Clare.** 1997. "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" *NBER Macroeconomics Annual* 12: 73–103.
- König, Michael, Kjetil Storesletten, Zheng Song, and Fabrizio Zilibotti.** 2022. "From Imitation to Innovation: Where Is All That Chinese R&D Going?" *Econometrica* 90 (4): 1615–54.
- Lopez-Martin, Bernabe.** 2017. "From Firm Productivity Dynamics to Aggregate Efficiency." *World Bank Economic Review* 30 (S1): S57–66.
- Midrigan, Virgiliu, and Daniel Yi Xu.** 2014. "Finance and Misallocation: Evidence from Plant-Level Data." *American Economic Review* 104 (2): 422–58.
- Moll, Benjamin.** 2014. "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?" *American Economic Review* 104 (10): 3186–221.
- National Bureau of Statistics of China.** 2005. "1% National Population Sample Survey in 2005" [dataset]. Unpublished data (accessed April 16, 2017).
- National Bureau of Statistics of China.** 2007. "Annual Surveys of Industrial Production" [dataset]. Unpublished data (accessed January 24, 2011).
- Ranasinghe, Ashantha.** 2014. "Impact of Policy Distortions on Firm-Level Innovation, Productivity Dynamics and TFP." *Journal of Economic Dynamics and Control* 46: 114–29.

- Restuccia, Diego, and Richard Rogerson.** 2008. "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments." *Review of Economic Dynamics* 11 (4): 707–20.
- Tombe, Trevor, and Xiaodong Zhu.** 2019. "Trade, Migration, and Productivity: A Quantitative Analysis of China." *American Economic Review* 109 (5): 1843–72.
- Vereshchagina, Galina.** 2023. "Financial Constraints and Economic Development: The Role of Firm Productivity Investment." *Review of Economic Dynamics*. <https://doi.org/10.1016/j.red.2023.01.005>.
- Yang, Mu-Jeung.** 2021. "Micro-level Misallocation and Selection." *American Economic Journal: Macroeconomics* 13 (4): 341–68.