Corporate financial structure, misallocation and total factor productivity

Uras, R.B.

Published in:
Journal of Banking & Finance

DOI:
10.1016/j.jbankfin.2013.11.011

Publication date:
2014

Document Version
Publisher's PDF, also known as Version of record

Journal of Banking & Finance 39 (2014) 177–191

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

Corporate financial structure, misallocation and total factor productivity ☆

Burak R. Uras *

Department of Economics, Tilburg University, European Banking Center and CentER, Room K 322B, P.O. Box 90153, 5000 LE Tilburg, The Netherlands

ARTICLE INFO

Article history:
Received 15 March 2013
Accepted 4 November 2013
Available online 20 November 2013

JEL classifications:
G11
G32
O47

Keywords:
Financial structure
Distortions
Misallocation
Total factor productivity

ABSTRACT

This paper studies the quantitative relevance of the cross-sectional dispersion of corporate financial structure in explaining the intra-industry allocation efficiency of productive factors. I solve a heterogeneous firms model with financial constraints and distortions to the marginal rental-rate of capital, and develop a measure for the intra-industry misallocation of factors of production. The distribution of capital rental rate and two types of firm-level balance sheet characteristics (pledgeability and liquid asset positions) determine the extent of misallocation and industry level total factor productivity (TFP). I calibrate the model using firm-level 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 cause quantitatively important industry level TFP losses.

1. Introduction

Understanding the rationale behind the empirically observed dispersion of financial structure across firms is a central research theme in corporate finance. The seminal article by Modigliani and Miller (1958) shows that when markets are complete, a firm's financial structure is not relevant for its economic performance; and therefore, the industry-wide dispersion of financial structure should not be related to the heterogeneity of firms's profitability. Following the Modigliani–Miller proposition, a non-exhaustive list of empirical studies have shown that weak financial conditions constrain access to capital at the firm level and deteriorate firm profitability when there are credit market imperfections.[1] In this paper, I contribute to the debate on financial structure and economic performance by exploiting a novel research angle: I study the relevance of corporate financial structure in explaining the cross-sectional allocation efficiency of productive resources in an economy with capital market imperfections.

The main purpose of my study is to quantify the importance of the dispersion in financial structure for the observed intra-industry misallocation of capital and labor in the US economy. I argue that weak balance sheet conditions and the resulting lax financial access generate inefficiencies in the intra-industry distribution of marginal products of capital and labor. These inefficiencies cause large TFP losses by inhibiting the reallocation of productive factors from large companies to small scale establishments.

To investigate the effects of the dispersion in financial structure on resource misallocation, I utilize a suitable heterogeneous firms model which accounts for the cross-sectional resource misallocation. Hsieh and Klenow (2009) develop a structural model to measure the misallocation generated by the heterogeneity of the distortionary wedges in capital rental rates. In this paper, I extend the Hsieh–Klenow set-up, and allow for firm-level financial structure idiosyncracies: Firms in the model are heterogeneous in their financial market ratings (pledgeability) and internal finance ability (liquidity). Financial constraints generated by weak financial positions together with capital rental rate distortions, a la Hsieh and Klenow (2009), drive wedges between marginal product of capital and labor across firms. In equilibrium, ceteris paribus, firms with low financial pledgeability and weak liquidity operate inefficiently small and labor intensive production units compared to firms with high financial pledgeability and strong liquidity. Capital rental-rate distortions augment the relation between financial structure and

☆ For their helpful suggestions and comments, I would like to thank Ping Wang, Bruce C. Petersen, Gaetano Antinolfi, Sebastian Galiani, and Yongseok Shin, conference participants at 2011 Econometric Society Meetings at Washington University in St. Louis, SAET Meetings in Faro Portugal and the seminar participants at Washington University in St. Louis Economics and Federal Reserve Bank of Philadelphia. All errors are mine.

* Tel.: +31 013 466 3650.
E-mail address: r.b.uras@uvt.nl

[1] Rajan and Zingales (1998), Eugene and French (2002), and Frank and Goyal (2003) provide empirical evidence on the effects of corporate financial structure for firm performance.

0378-4266/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jbankfin.2013.11.011

the labor intensity of production. I use measures of internal finance ability (asset liquidity) and financial pledgeability (bond ratings) to test the analytical predictions of the model by running a set of panel regressions for a sample of US firms from the Compustat database. The empirical study shows that low bond ratings and low asset liquidity are associated with labor intensive production and widening cross-sectional dispersion of marginal products.

I conduct a quantitative exercise to measure the effects of financial structure dispersion on cross-sectional allocation efficiency of productive factors for seven major US industry clusters. Similar Hsieh and Klenow (2009), I utilize two productivity concepts developed by Foster et al. (2008): *Revenue Productivity* and *Physical Productivity*. Revenue productivity (the product of physical productivity and a firm's output price) is an industry-wide deflator and should be equalized across firms in the absence of any distortions. The extent of revenue productivity dispersion is a measure for the misallocation of production factors. Higher cross-sectional variance of revenue productivity results in larger misallocation and associated TFP losses. With imperfect markets, as in Hsieh and Klenow (2009), the heterogeneity in capital rental rates generates a cross-sectional variance in individual revenue productivity. In the current model, financial access mitigates the distortionary effects of capital rental-rate heterogeneity and suppresses the cross-sectional variance of revenue productivity. I conduct a set of quantitative experiments for the following industry clusters: *Finance-Insurance and Real Estate*, *Information Technologies*, *Textiles and Fabrics*, *Food and Beverages*, *Minerals and Metal Manufacturing*, *Chemicals and Petroleum*, *Transportation Equipment*. Quantitative experiments show that when firm-level balance sheet positions (financial pledgeability and liquidity positions) are weakened to the same extent, for all financially constrained firms in a given industry, cross-sectional variance of the revenue productivity increases, which generates TFP losses of significant proportions. For example, in IT and Textile&Fabric industries, where dependence on external finance plays an important role in industry performance, shutting down financial access lowers aggregate industry TFP to as low as 50% of the pre-experiment level. This quantitative result suggests that the distribution of financial structure across firms is important for aggregate industry productivity when a large fraction of firms in the industry require external funds to mitigate the distortionary effects of capital rental-rates. This observation is in line with the findings of Rajan and Zingales (1998), who show that financial development is important for economic growth in industries where external finance dependence is high.

This paper is closely related to literature that measures the impact of factor misallocation on Total Factor Productivity. Recent studies have documented that misallocation of production factors can have sizeable quantitative effects on the aggregate total factor productivity. For example, Banerjee and Duflo (2005) show that the marginal product of capital differs widely among firms in India, which potentially reduces overall output, and Restuccia and Rogerson (2008) develop a model of firm dynamics and present calibration results for the US economy documenting that reallocation of resources, up to the point where marginal products are equalized across firms, could lead to substantial TFP gains. Using a cross-country approach, Hsieh and Klenow (2009) illustrate that if capital and labor are reallocated to equalize marginal products across production plants to the extent observed in the US, TFP gains for the manufacturing industry would be about 30–50% in China and 40–60% in India.

Similar to my paper, a number of other studies analyzed the interaction between financial frictions, non-financial distortions and aggregate economic performance. Buera and Shin (2013) study a neo-classical growth model with heterogeneous firms. Their study shows that when non-financial distortions are removed from the economy, the presence of financial distortions determines the speed of adjustment to the new steady-state. Midrigan and Xu (2013) present a parameterized growth model and demonstrate that financial constraints cannot account for a substantial fraction of the cross-country differences in factor misallocation and TFP. Pratap and Urrutia (2011) and Sandleris and Wright (2011) show that financial frictions can explain a significant fraction of the cross-country differences in factor misallocation and TFP during a financial crises. This paper also argues that access to finance can account for a significant fraction of the empirically observed factor misallocation and TFP losses when financial constraints exist in addition to distortions in capital rental rates. However, different from the existing studies in the literature, to the best of my knowledge, this paper is the first that exploits the empirically observed dispersion in corporate financial structure to explain factor misallocation and industry TFP.

The rest of the paper is organized as follows. Section 2 develops a heterogeneous firms model, which I apply to derive a disciplined measure of firm level distortionary wedges and firm's revenue productivity. Section 3 presents an empirical analysis showing firm level financial pledgeability and liquid asset positions of firms are important in determining the labor-intensity of production plants and firm-level revenue productivity. Section 4 quantifies the importance of financial structure dispersion in explaining firm-level input allocation distortions and the aggregate industry TFP. Section 5 discusses the main findings and concludes the paper.

2. The model

I study the extent of static TFP gains from resource reallocation as in Hsieh and Klenow (2009) by utilizing a heterogeneous firms model. Specifically, I assume that in the economy there is a finite number of industry level composite consumption good. These consumption goods are constant elasticity of substitution (CES) aggregates over a supply of differentiated intermediate products. The supply of intermediate products in the economy is exogenously determined. Differentiated intermediate good producers in each industry are heterogeneous in intrinsic productivity as well as in financial structure. There are credit market imperfections in the economy that determine the extent of real effects of financial structure on economic performance at the firm and also at the aggregate industry level. The details of production and the flow of funds in economy are as follows.

2.1. Composite consumption good production

The consumption good produced in an industry s, denoted by Y_s, is a CES aggregate over a fixed supply of differentiated intermediate products, Y_{si}, produced in the same industry

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}.$$

M_s measures the total number of differentiated input products in industry s, and σ is the constant elasticity of substitution across these input varieties. If we denote P_{si} as the unit price of the intermediate good supplied by a firm i for the industry s production, demand for each variety, Y_{si}^d, can be found from the standard cost minimization problem:

$$\min_{Y_{si}^d} \sum_{i=1}^{M_s} P_{si} Y_{si}^d, \text{ s.t. } Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}.$$

First order conditions from the industry level cost minimization problem lead to the individual variety demand functions

$$Y^d_{si} = \left(\frac{P_{si}}{P_s}\right)^{-\sigma} Y_s, \tag{1}$$

where $P_s = \left(\sum_{i=1}^{M_s} P_{si}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is the aggregate price in industry s. Having formulated the industry-level production decision, next we move onto the firm-level decisions concerning the provision of intermediate goods.

2.2. Intermediate goods production

Intermediate goods production requires labor (L) and capital (K) as productive inputs. The production function of a differentiated good producer i in sector s is given by a constant returns to scale production technology,

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}, \tag{2}$$

where $0 < \alpha_s < 1$ is an industry-level technology parameter that determines the capital share of production. Intermediate good producers are heterogeneous in (physical) factor productivity, A_{si}. A is distributed independently and identically across firms with a cumulative distribution function $F(A)$. Firms with high A are cost efficient in producing the intermediate good relative to firms with low A.

I abstract from household level decisions concerning labor-leisure trade-off: There is an exogenously set inelastic aggregate supply of labor denoted with L_s in each industry. The wage rate w is set exogenously as well. Therefore, firm level decisions do not have a general equilibrium effect on the level of wage compensation.

Similar to the supply of labor, there is also an exogenously determined aggregate capital stock in each industry denoted with K_s. Each intermediate good producer is endowed with a fraction of the aggregate capital stock, ζ_{si}, such that $\zeta_{si}K_s$ denotes individual capital holdings. Individual capital holdings of an intermediate good producer i from an industry s can be traded (leased or sold) to other intermediate good producers in the same industry s via a decentralized capital market. Both rental and purchase rates of capital are denominated in terms of the industry level composite consumption good. When capital is leased, a producer makes an ex-post transfer (after the production), whereas when it is purchased, the producer makes an ex-ante transfer (before the production). Ex-post transfer of capital (renting the capital good) is costly for some producers. I denote capital rental-rate distortions as Hsieh–Klenow type capital distortions. Capital market distortions create heterogeneity in capital rental prices. The capital rental rate charged to a producer i in industry s is $r^c(1+\tau_{si})$, where r^c is the average rental rate in the economy and τ is an idiosyncratic capital rental distortion drawn from a cumulative distribution function $G(\tau)$.

A differentiated goods producer i holds ω_{si} units of the (industry) consumption good in addition to the capital good. Similar to the capital good, consumption good holdings of a producer can be transferred to another producer in the same industry in exchange for capital. If the capital good is purchased, the buyer transfers R^c units of the composite consumption good to the seller prior to the production in return for each unit of the capital good purchased.

Differentiated good producers can also borrow the industry consumption good from other producers that operate in the same industry. However, there are constraints to the consumption good borrowing. The total consumption good that a producer can borrow, B_{si}, is constrained by the producer's financial pledgeability,

$$B_{si} \equiv (r^c(K_{si} - \zeta_{si}K_s) - \omega_{si}) \leqslant \theta_{si} R^c K_{si}, \tag{3}$$

where θ_{si} represents producer i's "financial market reputation" or his "financial pledgeability". Financial pledgeability determines the extent of financial leverage for a differentiated good producer. ω, ζ and θ have a joint cumulative distribution function $J(\omega, \zeta, \theta)$ across differentiated good producers. The inequality (3) is an exogenous borrowing constraint. As I will show below, the inequality (3) implies that only a fraction of the cost of external capital could be reduced by borrowing the consumption good from other producers and purchasing (instead of renting) the capital.

2.3. Optimizing behavior

There are two types of producers in each industry, denoted as *investors* and *lenders*. In equilibrium, there cannot be any producer who is both a lender and an investor at the same time. Lender producers have enough internal assets (capital and industry consumption good) to cover the optimum scale of capital investment; whereas, investor producers demand external finance to reach the optimum scale of investment.

I analyze a competitive equilibrium in the financial market at which lender producers are indifferent between leasing and selling the capital good. This no-arbitrage condition leads to the equalization of the rental and the purchase prices of capital, namely to $r^c = R^c = R$. Note that this equilibrium would prevail as long as there is not a shortage of consumption good holdings in the economy.

I define K^I_{si} as the amount of capital invested that is financed using the internal capital holdings of an investor type producer, and K^E_{si} as the amount of capital that is financed externally with $K^I_{si} + K^E_{si} = K_{si}$. External capital finance has two sources: (1) Leased capital at the unit rental rate of $r^s(1+\tau_{si})$ and (2) new capital purchases in exchange for consumption good that are subject to the borrowing constraint (3). The optimization problem of a producer i can be formulated as:

$$\begin{aligned}
\max_{P_{si}, K^E_{si}, K^I_{si}, L_{si}} \quad & \pi_{si} \equiv \{P_{si}A_{si}(K^E_{si} + K^I_{si})^{\alpha} L_{si}^{1-\alpha} - wL_{si} \\
& \qquad - R[(1+\tau_{si})(1-\theta_{si}) + \theta_{si}]K^E_{si} - RK^I_{si}\} \\
\text{s.t. } & K^I_{si} + K^E_{si} = K_{si} \\
& R(K_{si} - \zeta_{si}K_s) - \omega_{si} \leqslant \theta_{si} R K_{si}
\end{aligned}$$

Define $\lambda_{si} = \min\{\frac{\omega_{si} + R\zeta_{si}K_s}{RK_{si}}, 1\}$. $1 - \lambda_{si}$ fraction of a producer's capital investment is financed by (i) borrowing consumption good and exchanging it for capital good and (ii) by renting the capital good. Since the latter method of external financing is costly for a producer i with $\tau_{si} > 0$, in equilibrium a producer with a binding borrowing constraint exploits his borrowing capacity until its upper limit θ_{si} and finances $(1-\lambda_{si})\theta_{si}$ fraction of his capital investment via borrowing the consumption good. Therefore, for a differentiated good producer whose borrowing constraint is binding, the profit maximization problem reduces to the following:

$$\begin{aligned}
\max_{P_{si}, K_{si}, L_{si}} \quad \pi_{si} \equiv \{& P_{si}A_{si}K_{si}^{\alpha} L_{si}^{1-\alpha} - wL_{si} - R[\lambda_{si} + (1-\lambda_{si})[(1+\tau_{si})(1 \\
& - \theta_{si}) + \theta_{si}]]K_{si}\}.
\end{aligned} \tag{4}$$

The reduced form formulation of profit maximization problem has an intuitive interpretation. For a financially constrained firm, capital distortions and financing constraints affect the marginal cost of capital. Careful evaluation of the objective function (4) shows that the higher λ_{si}, or the higher θ_{si}, the lower is the marginal cost of production for an individual producer. Note that if either $\lambda_{si} = 1$ or $\theta_{si} = 1$, the marginal cost of capital for a producer i equals to R. If $\lambda_{si} < 1$ and $\theta_{si} < 1$, then the marginal cost of capital is greater than R as long as $\tau_{si} > 0$. Therefore, a firm i operating in industry s is financially constrained if for such a firm $\lambda_{si} < 1$ and $\theta_{si} < 1$ and $\tau_{si} > 0$.

The financial structure of a firm (internal finance opportunities and financial pledgeability) affects the external cost of capital. As I will show below, the effects of financial structure on the marginal cost can explicitly be isolated for firm-level pricing decision, firm-size and capital–labor choice. Specifically, for a differentiated good producer with a non-binding financing constraint (a producer whose marginal cost of capital equals to R), profit maximization with respect to the differentiated good price level, P^u_{si}, yields the standard condition that the optimal price is a fixed mark-up over marginal cost. That is,

$$P^u_{si} = \frac{\sigma}{1-\sigma}\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha}\frac{1}{A_{si}}. \tag{5}$$

On the other hand, for a producer with a binding financial constraint, we can derive the optimal pricing decision, P^c_{si}, as

$$P^c_{si} = \frac{\sigma}{1-\sigma}\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha} \times \frac{[\lambda_{si}+(1-\lambda_{si})[(1+\tau_{si})(1-\theta_{si})+\theta_{si}]]^{\alpha}}{A_{si}}. \tag{6}$$

From (5) and (6) we can observe financial constraints that drive the marginal cost of capital up and lead to $P^c_{si} > P^u_{si}$ such that

$$\frac{P^c_{si}}{P^u_{si}} = [\lambda_{si}+(1-\lambda_{si})[(1+\tau_{si})(1-\theta_{si})+\theta_{si}]]^{\alpha} > 1. \tag{7}$$

Using individual variety demand functions that I derived at Eq. (1), this in turn implies a gap in total quantity produced between a constrained and unconstrained firm such that,

$$\frac{Y^c_{si}}{Y^u_{si}} = [\lambda_{si}+(1-\lambda_{si})[(1+\tau_{si})(1-\theta_{si})+\theta_{si}]]^{-\sigma\alpha} < 1. \tag{8}$$

Similarly, the profit maximizing capital–labor ratio for an unconstrained firm, k^u_{si}, is derived as

$$k^u_{si} \equiv \left(\frac{K_{si}}{L_{si}}\right)^{u} = \frac{\alpha}{1-\alpha}\frac{w}{R}. \tag{9}$$

For a constrained firm the capital–labor ratio, k^c_{si}, is found as

$$k^c_{si} \equiv \left(\frac{K_{si}}{L_{si}}\right)^{c} = \frac{\alpha}{1-\alpha}\frac{w}{R}\frac{1}{[\lambda_{si}+(1-\lambda_{si})[(1+\tau_{si})(1-\theta_{si})+\theta_{si}]]}. \tag{10}$$

Evaluating Eqs. (9) and (10) we can show that financially constrained firms are labor intensive compared to unconstrained firms. The relative labor intensity of constrained firms is found as

$$\frac{k^c_{si}}{k^u_{si}} = \frac{1}{[\lambda_{si}+(1-\lambda_{si})[(1+\tau_{si})(1-\theta_{si})+\theta_{si}]]}. \tag{11}$$

Using equality (9), we can infer distortions to the capital–labor ratio for differentiated good producers with binding financing constraint as

$$1+\underbrace{\tau_{si}(1-\theta_{si})(1-\lambda_{si})}_{\equiv\gamma_{si}} = \frac{\alpha}{1-\alpha}\frac{w}{R}\frac{L_{si}}{K_{si}}. \tag{12}$$

The Eq. (12) shows that distortions to capital–labor ratio (γ_{si}) has three components. The first component (τ_{si}) generates the heterogeneity in capital rental rates. Antunes et al. (2008) interpret this distortion as the *financial repression*. The second component (θ_{si}) is associated with the ability to borrow against investment returns, which Matsuyama (2007) defines as individual *financial pledgeability*. Finally, the third component (λ_{si}) is associated with the (in) ability to finance investment projects using internal *liquidity*. Straightforward application of comparative-statics yields the following properties of γ_{si} : γ_{si} increases in capital rental rate distortions faced by a firm i (τ_{si}) and decreases by the amount of internal financing the firm can provide (λ_{si}) and by financial pledgeability (θ_{si}). These analytical results show that low financial pledgeability, low internal financing ability, and high capital market distortions are associated with labor intensive production. We can also derive the following cross-partial derivatives,

$$\frac{\partial\gamma^2_{si}}{\partial\tau_{si}\partial\theta_{si}} < 0$$

$$\frac{\partial\gamma^2_{si}}{\partial\tau_{si}\partial\lambda_{si}} < 0$$

$$\frac{\partial\gamma^2_{si}}{\partial\theta_{si}\partial\lambda_{si}} > 0$$

Cross-partial derivatives show that the effects of an incremental change in financial pledgeability (and internal finance ability) is greater for firms that face high capital rental distortions. More importantly, as an empirically testable prediction of the model, the effects of a rise in financial pledgeability on capital–labor ratio distortions are more pronounced for firms with high external finance use. The empirical study in Section 3 will build upon these analytical predictions that we derive from the model.

For financially constrained firms, $\gamma_{si} > 0$ holds. The quantitative analysis below will study hypothetical changes to the financial structure of financially constrained firms. Since I will study the macroeconomic implications of the distribution of financial structure, I will also allow for financially unconstrained firms in the economy to have negative capital–labor distortions ($\gamma_{si} \le 0$). For firms with $\gamma_{si} \le 0$ (unconstrained firms), financial structure does not have any influence on pricing (and quantity produced) and capital–labor ratio.

2.4. Equilibrium

The allocation of resources across differentiated good producers not only depends on the distribution of physical productivity, but also on the distribution of financial structure that determines the extent of the effects of capital rental-rate distortions and financing constraints on firm size. Therefore, the total capital and labor employed by each producer is proportional to the magnitude of firm-level capital–labor distortions γ_{si}, and physical productivity A_{si}. Specifically, both K_{si} and L_{si} are proportional to $\frac{A_{si}}{(1+\gamma_{si})^{\sigma\alpha}}$ and for financially constrained firms they are proportional to $\frac{A_{si}}{[\lambda_{si}+(1-\lambda_{si})[(1+\tau_{si})(1-\theta_{si})+\theta_{si}]]^{\sigma\alpha}_{si}}$.

Marginal revenue productivity of capital (MRPK) is proportional to the capital–labor distortions, such that

$$\text{MRPK}_{si} \propto R[1+\gamma_{si}],$$

where for constrained firms MRPK is proportional to the financial structure and the level of capital rental-rate distortions:

$$\text{MRPK}^c_{si} \propto R[\lambda_{si}+(1-\lambda_{si})[(1+\tau_{si})(1-\theta_{si})+\theta_{si}]].$$

Since there are no distortions in the labor market, for all firms the marginal revenue product of labor is not associated with capital–labor distortions

$$\text{MRPL}_{si} \propto w.$$

I study a partial equilibrium for this economy: The wage rate w and the interest rate R are exogenously determined. The aggregate labor and capital supply available for each industry equals to the aggregate demand of labor and capital, such that

$$L_s = \sum_{i=1}^{M_s} L_{si},$$

$$K_s = \sum_{i=1}^{M_s} K_{si}.$$

In the next section, I test the analytical predictions of the model using a panel data analysis and identify characteristic features in firm's financial structure (namely, internal asset liquidity and financial pledgeability) that are influential on capital–labor distortions (γ_{si}'s). In Section 4, I derive aggregation results, a lá Hsieh and Klenow (2009), and calibrate the economy, described in Section 2, for the US firm level data from Compustat, and I study the properties of aggregate TFP with respect to changes in the distribution of firm-level financial structure.

3. Empirical study

In this section, using a sample of US manufacturing firms from Compustat North America, I test the analytical predictions of the model developed in the previous section.[2] The hypotheses to be tested are as follows:

- Poor financial pledgeability is associated with labor intensive production.
- Poor financial liquidity is associated with labor intensive production.

3.1. The data

The sample is extracted from Compustat North America. The firms contained in the sample are active firms as of 2006. The time series dimension covers the time period 1990–2006. The firms in the sample are chosen in such a way that as of 2006 each firm has spent at least 5 years in the database. There are 725 such firms in our sample. The summary statistics about the sample distribution of the firms can be found in Table 1.

3.2. Estimation

I estimate the following reduced form regression equations with time varying industry fixed effects γ_{st} to study the sensitivity of capital–labor distortions to firm level financial pledgeability and financial liquidity[3]:

$$KLDistort_{it} = \gamma_{st} + \eta_1^{*} Fin.\ Liquidity_{it}^{*} EFD_i + \beta^{*} Controls_{it} + \epsilon_{it} \quad (13)$$

$$KLDistort_{it} = \gamma_{st} + \eta_2^{*} Fin.\ Pledgeability_{it}^{*} EFD_i + \beta^{*} Controls_{it} + \epsilon_{it} \quad (14)$$

$KLDistort_{it}$ represents deviations from optimal capital–labor ratio respectively for firm i in period t. $KLDist_{it}$ is generated using the γ_i variable derived in Section 2. That is:

$$KLDist_{it} = \gamma_{it} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{R}\frac{L_{it}}{K_{it}} - 1,$$

where α_s is the 3-digit industry specific capital share. wL_i, "compensation of employees", is available in Compustat as "Labor and Related expenses", K_i, capital stock, is derived from "Property, Plant and Equipment" and "Capital Expenditures" data items in Compustat using the methodology developed in Chirinko et al. (2007). R, the return to capital, is taken as 10% as in Hsieh and Klenow (2009). A high value of $KLDist_{it}$ means high distortions to the capital costs, and more labor intensive production.

The right hand side variables included in the regression analysis are as the following:

- $Fin.\ Liquidity_{it}$ captures firm level financial liquidity. Financial liquidity is measured as

$$(Current\ Assets - Current\ Liabilities)/(Current\ Liabilities)_{it}.$$

- $Fin.\ Pledeability_{it}$ captures financial pledgeability of firm i in year t. Financial pledgeability is proxied with two different measures:
  1. *Credit Rating*; measured as $log(Long\ Term\ Domestic\ Credit\ Issuer\ Rating)$ reported by Standard and Poor's in Compustat Database. Firm credit ratings in the sample range from $C = 2$ to $AAA = 24$, with $C = 2$ being the worst credit rating and $AAA = 24$ being the best credit rating. The mean (and also median) rating in the sample is $B- = 12.1$.
  2. And, with $log\ (Net\ Worth) * log\ (Credit\ Rating)$, where *Net Worth* is measured as $(log(1 + Total\ Assets - Total\ Debt))$.

The purpose of having these two different degrees of financial pledgeability is as the following: Firms which receive low credit ratings ex ante due to repayment problems, if continue to borrow and choose to operate with low financial net worth, are expected to face higher cost of external financing due to the moral hazard problem associated with high borrowing and low probability of repayment of the amount borrowed.

- I test the sensitivity of K/L distortions to financial characteristics with respect to the interactive effect of industry external finance dependence.As it has been shown in the analytical section, firms with high uses of external finance are expected to be more labor intensive in the face of low financial pledgeability. Therefore, it is crucial to consider the presence of external finance dependence heterogeneity across industries while studying the sensitivity of capital–labor ratio distortions with respect to financial pledgeability. To serve this purpose, using 3-digit NAICS codes, I group industries according to their external finance dependence levels and create an "external finance dependency" (EFD) dummy variable: As in Rajan and Zingales (1998), I define the average external finance dependence ($AEFD$) of industry j as: $AEFD_j = (Avg\{(Cash\ \ Flow\ \ From\ \ Operations - Cap\ Exp)/(Cap\ Exp)_i)\}_{i=1}^{N_j}$, where $i \in \{1, \ldots, N_j\}$ are firms operating in industry j. $(External\ Finance\ Dependence)_2 = 1$ and 0 otherwise if $0.3 < AEFD_j < 0.6$. $(External\ Finance\ Dependence)_3 = 1$ and 0 otherwise if $AEFD_j > 0.6$.

Hence, firms operating in industries with low external finance dependence have: $(External\ Finance\ Dependence)_2 = (External\ Finance\ Dependency)_3 = 0$, firms in industries with intermediate levels of external finance dependency have $(External\ Finance\ Dependence)_2 = 1$ and $(External\ Finance\ Dependence)_3 = 0$, and

Table 1
Summary statistics.

Variable	Mean	Standard deviation	Median
Size (#(employees))	1926	576	349
Capt.–lab. distortions	8.82	2.11	5.81
Credit rating	12.1(=B-)	4.4	12(=B-)
Net worth (millions of $'s)	121.11	591.22	191.12
Financial liquidity	0.39	0.12	0.18
Profitability (millions of $'s)	1.45	1.10	0.85
Firm age	18.2	5.1	12.9
Liability structure	0.23	0.09	0.18
Research and development intensity	0.08	0.04	0.06

Compustat Industrial Annual, Average of 1990–2006. Firm size is derived using the total number of employees at an establishment. Capital–Labor distortions are derived using the model presented in Section 2. Credit rating is the S&P long term domestic credit issuer rating. Net worth is computed as *Total Assets – Total Debt*. Financial Liquidity is computed as $(Current\ Assets - Current\ Liabilities)/Current\ Liabilities$. Profitability is $(Total\ Sales - Total\ Cost\ of\ Goods\ Sold)/Size$, firm age proxied using the total number of years an establishment has spent in the database. Liability structure refers to the debt structure $Total\ Long\ Term\ Debt/Total\ Debt$ of a particular firm i in year t. Research and Development intensity of a firm i in year t, and is computed as $R\&D\ Expenditures/Total\ Sales$.

[2] The data used in this analysis will be available by the author upon request.
[3] I use 3-digit NAICS codes.

firms in industries with high levels of external finance dependency have $(External\ Finance\ Dependence)_2 = 0$, $(External\ Finance\ Dependency)_3 = 1$.

Other control variables included in the regression analysis are as the following:

- $Size_{it}$ refers to the employee size of the firm in year t.
- $Profitability_{it}$ captures the effects of firm profitability and it is proxied with $((Total\ Sales - Total\ Cost\ of\ Goods\ Sold)/Size)$.
- $FirmAge_{it}$ refers to the total number of years the firm i spent in the database until year t.
- $LiabStr_{it}$ refers to the debt structure as $Total\ Long\ Term\ Debt/Total\ Debt$ of a particular firm i in year t.
- $R\&DInt_{it}$ is the Research and Development intensity of a firm i in year t, and is computed as $R\&D\ Expenditures/Total\ Sales$.

To control for outlier effects I trim the upper and lower 1% tails of each distribution.

3.3. Estimation results

I estimate the model for the full sample, as well as for large, medium size, and small firms separately. Small firms refer to those firms which have less than 500 employees in their establishments, medium-size firms have a total number of employees between 500 and 5000, and large firms have more than 5000 employees. Tables 2a,2b,2c,2d report the estimation results from Ordinary-Least-Squares (OLS) regressions.[4]

Table 2a provides empirical results which are in line with the predictions of the analytical model. Financial pledgeability is important for determining the firm level capital–labor ratio distortions from an optimum benchmark. Coefficient estimates associated with credit ratings and the interactive term between credit ratings and net worth enter regression equations with expected signs; that is the better the financial pledgeability of a firm the smaller are the distortions to the choice of capital–labor ratio, and hence the production units are relatively more capital intensive. The interactive term between net worth and credit ratings in fact not only enters the regression equation with the expected sign but also much more significantly. The results are relatively more significant for those firms which operate in relatively more external finance dependent sectors. Also, as the analytical results presented in Section 3 suggested, the effects of financial pledgeability on capital–labor ratio distortions are higher the larger are the capital rental distortions.

Similarly, financial asset liquidity enters regression equations as a significant explanatory variable especially for those firms which operate in highly external finance dependent industries.

Profitability and firm age are not significant determinants of capital–labor ratio distortions. Firm size and liability structure on the other hand are significant determinants of capital–labor ratio distortions because these two variables are expected to contain information regarding the financial characteristics of an individual firm.

The effects of financial asset liquidity on capital–labor ratio distortions does not vary across firm size classes. However, Tables 2b–2d show the effects of financial pledgeability on capital–labor ratio distortions are much more pronounced for firms of smaller scale. A plausible explanation for this outcome is that the firm size influences the effects of financial characteristics on real performance. The size of a firm could have an implicit reputation effect which makes the observed "financial reputation" matter more for firms with a smaller size.

4. Quantitative analysis

I conduct quantitative exercises to study the implications of the dispersions in financial pledgeability and asset liquidity for the productivity dispersion and aggregate total factor productivity at the industry level.

In order to stress the importance of capital rental distortions (τ_{si}), financial pledgeability (θ_{si}) and asset liquidity (λ_{si}) for industry-wide total factor productivity, I employ the concepts "physical productivity" and "revenue productivity" which Foster et al. (2008) call as TFPQ and TFPR respectively. Firm level physical and revenue productivity in this current setting can be defined as in Hsieh and Klenow (2009). Namely, for a firm i operating in sector s:

$$TFPR_{si} \equiv P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_{si}}(wL_{si})^{1-\alpha_{si}}},$$

and

$$TFPQ_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_{si}}(wL_{si})^{1-\alpha_{si}}},$$

with

$$A_{si} = \mu^{1-\alpha}\frac{(P_sY_s)^{-\frac{1}{\sigma-1}}}{P_s}\frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}L_{si}},$$

where μ is a constant and equals to $w^{1-\alpha_s}(P_sY_s)^{-\frac{1}{\sigma_1}}/P_s$. In this model, as in Hsieh and Klenow (2009), TFPR is constant across plants within an industry, unless plants face distortionary capital rental rates or have differential financial pledgeability or asset liquidity levels. In the absence of financial characteristic heterogeneity, more capital and also labor should be allocated to plants with high levels of TFPQ. Denoting marginal revenue product of capital and labor with $MPRK_{si}$ and $MPRL_{si}$ respectively, one can show that plant TFPR is proportional to a geometric average of a plant's (operating in industry s) marginal revenue products of capital and labor as

$$TFPR_{si} \propto (MRPK_{si})^{\alpha_s}(MRPL_{si})^{1-\alpha_s} \propto (1+\gamma_{si})^{\alpha_s}. \tag{15}$$

Furthermore, for a financially constrained firm, namely for firms with $\gamma_{si} > 0$

$$TFPR_{si} \propto (MRPK_{si})^{\alpha_s}(MRPL_{si})^{1-\alpha_s} \propto (1+\tau_{si}(1-\theta_{si})(1-\lambda_{si}))^{\alpha_s}. \tag{16}$$

For constrained firms, $TFPR_{si}$ is increasing in capital rental rate distortions, but decreasing in financial pledgeability and in financial asset liquidity. High plant TFPR signals that the plant confronts capital market barriers which raises firm level marginal products. In my model, financial pledgeability and asset liquidity mitigate the capital market barriers an individual plant owner faces.

We can develop the industry-wide aggregate TFP formula as follows

$$TFP_s = \left(\sum_{i=1}^{M_s}\left(A_{si}\frac{\overline{TFPR}_s}{TFPR_si}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}, \tag{17}$$

with

$$\overline{TFPR}_s = \left[\frac{R}{\alpha_s}\sum_{i=1}^{M_s}(1+\gamma_{si})\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)\right]^{\alpha_s}\left[\frac{1}{1-\alpha_s}\sum_{i=1}^{M_s}\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)\right]^{1-\alpha_s}, \tag{18}$$

[4] Firms with low levels of capital are expected to have relatively high levels of asset/liability ratio due to insufficient amounts of collateral to back-up their borrowing. Therefore, in order to control for this possible endogeneity problem, I estimate the model using the 2-stage least squares estimation methodology by using one period lagged values of net worth and credit rating as instrumental variables. 2SLS results confirm the findings from OLS regressions. The tables containing the results from 2SLS estimation can be found in the accompanying Online-appendix of this paper.

Table 2a
OLS (Panel) with full sample. Dependent variable: distortions to *K*/*L* ratio.

Fin liquidity$_{lowEF}$	−0.218 (−1.05)	–	–
Fin liquidity$_{midEF}$	−0.241* (−1.99)	–	–
Fin liquidity$_{hiEF}$	−0.267* (−2.03)	–	–
ln (CrRat)$_{lowEF}$	–	−0.219 (−0.98)	–
ln (CrRat)$_{midEF}$	–	−0.276 (−0.76)	–
ln (CrRat)$_{hiEF}$	–	−0.398 (−1.61)	–
ln (1 + NWorth) ∗ ln (CrRat)$_{lowEF}$	–	–	−0.522 (−1.23)
ln (1 + NWorth) ∗ ln (CrRat)$_{midEF}$	–	–	−0.601** (−3.65)
ln (1 + NWorth) ∗ ln (CrRat)$_{hiEF}$	–	–	−0.721** (−4.21)
ln (Size)	−0.425** (−5.34)	−0.441** (−5.67)	−0.493** (−3.71)
Profitability	−0.063 (−0.34)	−0.071 (−0.45)	−0.064 (−0.61)
ln (1 + FirmAge)	−0.581 (−1.16)	−0.574 (−0.96)	−0.576 (−0.91)
LiabStr	0.712** (3.46)	0.721** (3.91)	0.732* (2.11)
R&D Int	0.754** (2.34)	0.729** (3.01)	0.741** (3.13)
R^2	0.367	0.389	0.312

The values in parentheses are robust *t*-statistics. Subscripts (lowEF), (midEF), (hiEF) refer to the sensitivity of capital labor distortions with respect to financial pledgeability for firms operating in industries with low, medium, and high level external finance dependency sector respectively. FirmAge is proxied using the total number of years an establishment has spent in the database. See the notes to Table 1.
* Indicates significance at 10%.
** Indicates significance at 5%.

Table 2b
OLS (Panel) with large firms. Dependent variable: distortions to *K*/*L* ratio.

Fin liquidity$_{lowEF}$	−0.143 (−0.79)	–	–
Fin liquidity$_{midEF}$	−0.201 (−1.82)	–	–
Fin liquidity$_{hiEF}$	−0.232* (−2.11)	–	–
ln (CrRat)$_{lowEF}$	–	0.984 (0.78)	–
ln (CrRat)$_{midEF}$	–	1.381 (0.88)	–
ln (CrRat)$_{hiEF}$	–	1.255 (0.87)	–
ln (1 + NWorth) ∗ ln (CrRat)$_{lowEF}$	–	–	−0.671 (−1.23)
ln (1 + NWorth) ∗ ln (CrRat)$_{midEF}$	–	–	−0.912 (−1.47)
ln (1 + NWorth) ∗ ln (CrRat)$_{hiEF}$	–	–	−0.985 (−1.65)
ln (Size)	1.198* (2.01)	1.231* (2.42)	1.019* (2.22)
Profitability	−0.009 (−0.19)	−0.042 (−0.22)	−0.101 (−0.17)
ln (1 + Firm age)	1.112 (0.76)	1.231 (0.32)	0.981 (0.78)
LiabStr	1.891* (2.12)	2.011* (1.99)	1.982* (2.07)
R&D Int	0.912 (1.54)	1.104 (1.82)	1.184 (1.63)
R^2	0.391	0.384	0.389

Large firms are those establishments with more than 5000 employees. See also the notes to Table 2a.

Table 2c
OLS (Panel) with medium size firms. Dependent variable: distortions to *K*/*L* ratio.

Fin liquidity$_{lowEF}$	−0.021(−1.71)	–	–
Fin liquidity$_{midEF}$	−0.191** (−2.51)	–	–
Fin liquidity$_{hiEF}$	−0.381** (−2.69)	–	–
ln (CrRat)$_{lowEF}$	–	−0.113 (−1.05)	–
ln (CrRat)$_{midEF}$	–	−0.179 (−1.67)	–
ln (CrRat)$_{hiEF}$	–	−0.175* (−1.98)	–
ln (1 + NWorth) ∗ ln (CrRat)$_{lowEF}$	–	–	−0.665** (−2.78)
ln (1 + NWorth) ∗ ln (CrRat)$_{midEF}$	–	–	−0.781** (−4.69)
ln (1 + NWorth) ∗ ln (CrRat)$_{hiEF}$	–	–	−0.759** (−5.81)
ln (Size)	−0.231** (−6.11)	−0.314** (−6.71)	−0.367** (−6.01)
Profitability	−0.098 (−0.11)	−0.182 (−0.18)	−0.241 (−0.21)
ln (1 + Firm age)	−0.212 (−1.01)	−0.174 (−1.02)	−0.161 (−0.89)
LiabStr	0.681** (4.12)	0.711** (4.64)	0.981** (4.91)
R&D Int	0.661** (3.43)	0.771** (3.72)	0.712** (3.65)
R^2	0.345	0.351	0.342

Medium size firms are those establishments with more 500 and less than 5000 employees. See also the notes to Table 2a.

where for constrained ($\gamma_{si} > 0$) firms

$$TFPR_{si} = \left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{1}{1-\alpha_s}\right)^{1-\alpha_s}(1+\tau_{si}(1-\theta_{si})(1-\lambda_{si})), \tag{19}$$

and for unconstrained ($\gamma_{si} < 0$) firms

$$TFPR_{si} = \left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{1}{1-\alpha_s}\right)^{1-\alpha_s}(1+\gamma_{si}). \tag{20}$$

When TFPQ and TFPR are jointly log-normally distributed, as Hsieh and Klenow (2009) has shown, there is a simple closed form expression for industry-wide aggregate TFP as:

$$\log TFP_s = \frac{1}{1-\sigma}\log\left(\sum_{i=1}^{M_s}A_{si}^{\sigma-1}\right) - \frac{\sigma}{2}var(logTFPR_{si}). \tag{21}$$

Table 2d
OLS (Panel) with small firms. Dependent variable: distortions to K/L ratio.

Fin liquidity$_{lowEF}$	−0.113 (−1.43)	–	–
Fin liquidity$_{midEF}$	−0.234** (−3.11)	–	–
Fin liquidity$_{hiEF}$	−0.461** (−3.91)	–	–
ln (CrRat)$_{lowEF}$	–	−0.126 (−1.45)	–
ln (CrRat)$_{midEF}$	–	−0.191 (−1.63)	–
ln (CrRat)$_{hiEF}$	–	−0.211 (−1.84)	–
ln (1 + NWorth) * ln (CrRat)$_{lowEF}$	–	–	−0.4 31* (−2.04)
ln (1 + NWorth) * ln (CrRat)$_{midEF}$	–	–	−0.749** (−5.13)
ln (1 + NWorth) * ln (CrRat)$_{hiEF}$	–	–	−0.912** (−6.74)
ln (Size)	−0.321** (−5.67)	−0.378** (−5.99)	−0.441** (−5.61)
Profitability	−0.121 (−0.21)	−0.212 (−0.23)	−0.211 (−0.29)
ln (1 + Firm age)	−0.301 (−1.21)	−0.281 (−1.11)	−0.291 (−1.22)
LiabStr	0.731** (5.32)	0.792** (5.41)	0.873* (5.36)
R&DInt	0.701** (3.91)	0.785* (3.89)	0.816** (3.84)
R^2	0.310	0.293	0.296

Small firms are those establishments with less than 500 employees. See also the notes to Table 2a.

In the next section, using Compustat data, I will provide counterfactual policy experiments to study the effects of (1) capital rental rate distortions (τ_{si}), (2) financial pledgeability (θ_{si}), and (3) asset liquidity (λ_i) on firm productivity dispersion (TFPR dispersion) for seven major US industry clusters.

4.1. Data and counterfactual experiments

I use the same Compustat sample from the empirical analysis for the computational exercise.[5] I use data from 725 firms which were active between the 2003 and 2006 time period; however, I concentrate on seven major industry groups in the policy analysis. Each firm level observation is taken as a time-series average over the 2003–2006 data observations. Each firm was active with reported necessary balance sheet data for the 2003–2006 time period.

I apply the proxies for financial pledgeability (θ_{si}) and asset liquidity (λ_{si}) developed in the previous section to back out firm level distortions to capital rental rates (τ_{si}) for financially constrained firms.

The analytical model developed in Section 3 provided that, for constrained firms,

$$1 + \underbrace{\tau_{si}(1-\theta_{si})(1-\lambda_{si})}_{\gamma_{si}} = \frac{\alpha}{1-\alpha}\frac{w}{R}\frac{L_{si}}{K_{si}}$$

is a disciplined measure of observed firm level capital–labor distortions which we can compute using balance sheet data from Compustat database. In order to derive τ_{si} for each firm using the observed capital–labor distortions γ_{si}, I map financial pledgeability and asset liquidity level of each firm observed in the data to an index between $[0, 1]$ where I apply the following functional forms for this transformation:

- For financial pledgeability:

  $M(Credit\ Rating)^{\zeta_p}$

where Credit Rating is the S&P Long Term Domestic Issuer Credit Rating of an individual firm from the Compustat database,

- For asset liquidity:

  $N(B + Financial\ Liquidity)^{\zeta_\ell}$

where Financial Liquidity is (Current Assets − Current Liabilities)/Current Liabilities for a firm.

In these functional forms the parameters $M, \zeta_p, N, \zeta_\ell$, and B are chosen in such a way that the transformed distributions mimic the observed distributions as closely as possible in terms of the mean/standard deviation ratio as well as the skewness. The values assigned to functional form parameters are: $M = (1/28)^{0.84}$, $\zeta_p = 0.84, N = (1/15)^{0.68}, \zeta_\ell = 0.68$, and $B = 5$. Using λ_{si} and θ_{si} we can derive capital rental distortions for each financially constrained firm i, τ_{si}, as:

$$\tau_{si} = \frac{\gamma_{si}}{(1-\lambda_{si})(1-\theta_{si})}. \tag{22}$$

We can derive $A_{si} = TFPQ$ for each firm using

$$A_{si} = \mu^{1-\alpha}\frac{(P_sY_s)^{-\frac{1}{\sigma-1}}}{P_s}\frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}L_{si}}$$

where $\mu = w^{1-\alpha_s}(P_sY_s)^{-\frac{1}{\sigma-1}}/P_s$. Since in Compustat data, only values are observable and not the prices, as in Hsieh and Klenow (2009), I assume $\mu = 1$. To derive firm level TFPR I use:

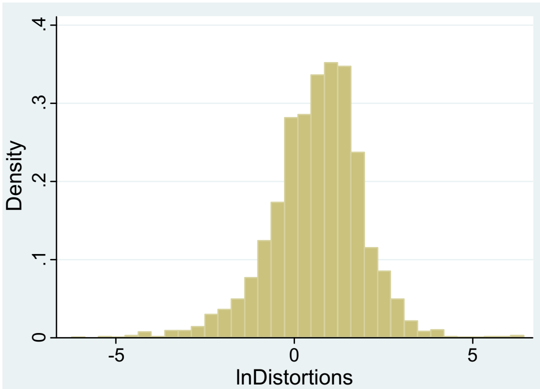
$$TFPR_{si} \equiv P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_{si}}(wL_{si})^{1-\alpha_{si}}}.$$

Figs. 1–8 show distributions of observed capital–labor distortions (γ_{si}), capital–rental distortions τ_{si}, observed financial pledgeability (long term credit ratings), implied financial pledgeability transformation θ_{si}, observed asset liquidity, implied asset liquidity transformation λ_{si}, and finally TFPQ and TFPR at the firm level for the full sample, as well as for firms with less than 2200 employees and for firms with more than 2200 employees separately, where 2200 is the mean employment size of the sample.

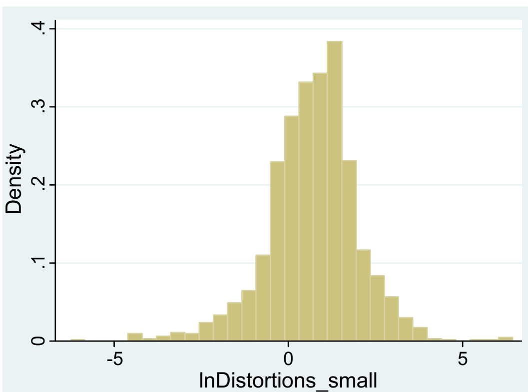
Sample distributions show that, as Foster et al. (2008) has documented, firms face heterogeneous capital rental distortions which implies dispersion in firm productivity levels. In Figs. 1b and c and 2b and c, we can observe that although large firms's distribution first order stochastically dominates that of small firm's, both large and small firms do face distortionary capital rental rates which affect their capital–labor choice. As a result we observe a TFPR dispersion for both small and large firms.

We can derive industry TFPRS and TFP using Eqs. (18) and (21). Table 3 lists the industry-wide properties of TFP, TFPRS, as well as capital–labor ratio distortions. Fig. 9 plots ln (TFPRS) vs ln (TFPS) and documents that there is a close correlation between industry-wide physical productivity and the revenue productivity. Table 3 and Fig. 9 show that there is substantial heterogeneity in industry TFPS as well as industry $\overline{TFPRS}$ across 3-digit NAICS industries. Therefore, in order to study the contribution of financial characteristics (financial pledgeability and financial asset liquidity) for aggregate economic performance it is crucial to concentrate on major 3-digit NAICS industries.

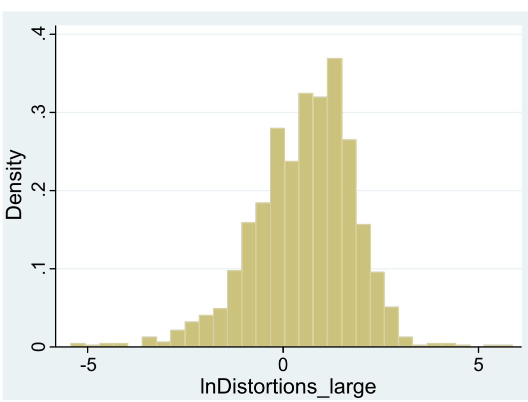
[5] The data used in this analysis will be available by the author upon request.



(a) Sample Distribution of Distortions to K/L Ratio

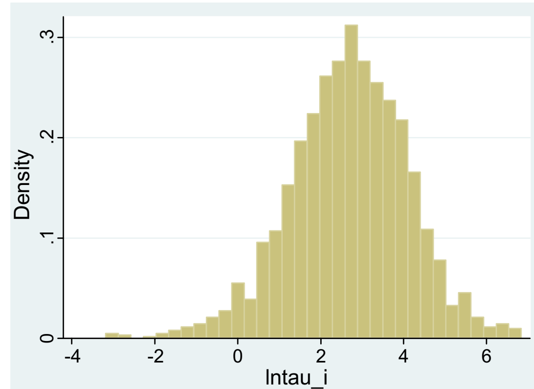


(b) Sample Distribution of Distortions to K/L Ratio – Small Firms

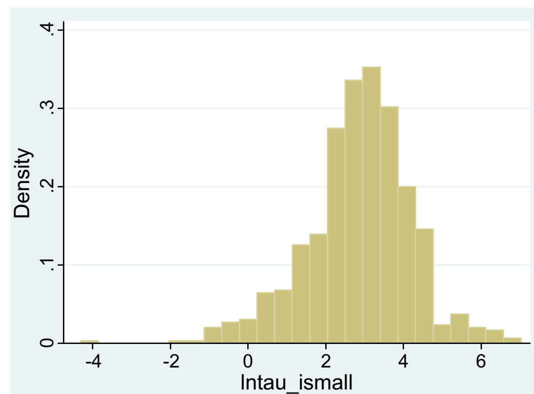


(c) Sample Distribution of Distortions to K/L Ratio – Large Firms

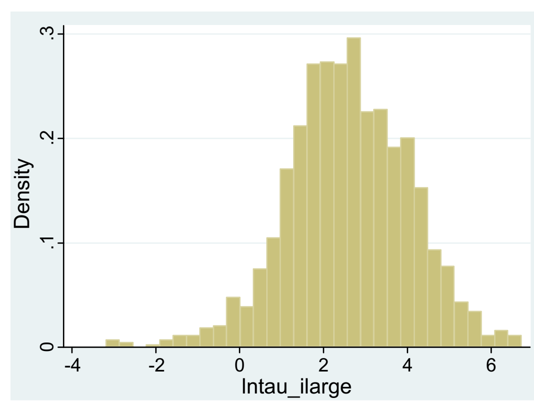
Fig. 1. lnDistortions is the natural log of observed K/L distortions in the Compustat data which are derived using the deviations from the optimum K/L ratio. The data is cross-sectional. Each firm level observation is derived using time series K/L distortion averages over 2003–2006. Small firms are production plants with less than 2200 employees. Large firms are production plants with more than 2200 employees. 2200 Employees is the mean employment size of the sample firms.



(a) Sample Distribution of Capital Rental Rate Distortions



(b) Sample Distribution of Capital Rental Rate Distortions – Small Firms



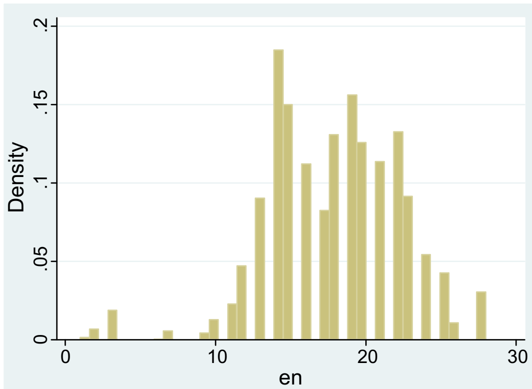
(c) Sample Distribution of Capital Rental Rate Distortions – Small Firms

Fig. 2. lnTau is the natural log of firm level capital rental rate distortions which are backed-out using K/L distortions, financial pledegeability and asset liquidity index.

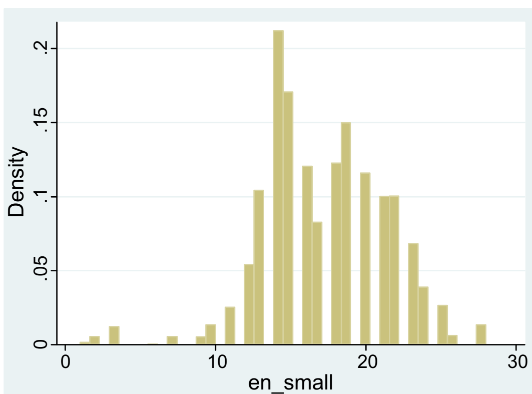
For this purpose, I conduct the counterfactual experiments for 7 major industry branches as listed in Tables 4 and 5. The industry clusters in hand are:

1. Information Technology (IT): Machinery Manufacturing; Computer and Electronic Product Manufacturing.
2. FIRE: Credit Intermediation and Related Services; Securities, Commodity Contracts, and other Financial Investments and Related Activities; Insurance Carriers and Related Activities; Retail Trade; Real Estate.
3. Food and Beverages (FB): Food and Kindred Products; Beverages and Tobacco Products.
4. Textiles and Fabrics (TX): Textiles and Fabrics.
5. Chem and Petroleum (CP): Petroleum and Coal Products Manufacturing; Chemical Manufacturing.
6. Metal and Mineral (MM): Nonmetallic Mineral Product Manufacturing; Primary Metal Manufacturing.
7. Transportation Equipment (TE): Transportation Equipment Manufacturing.

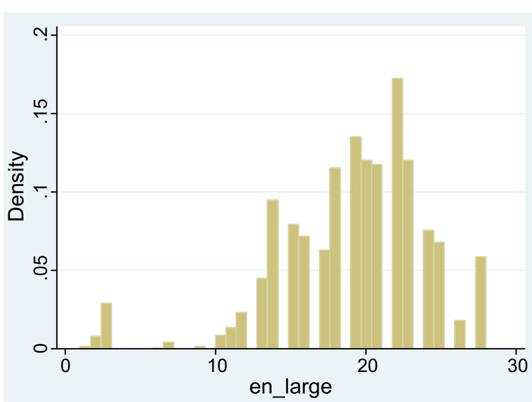
For these seven major industry clusters, I study the following two counterfactual experiments:



(a) Sample Distribution of Credit Ratings

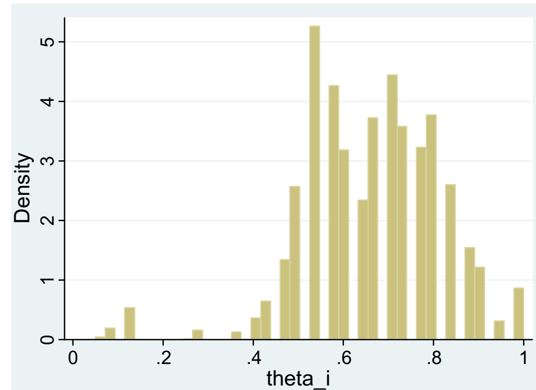


(b) Sample Distribution of Credit Ratings – Small Firms

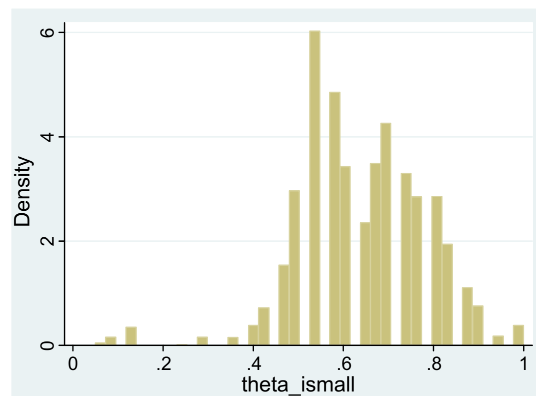


(c) Sample Distribution of Credit Ratings – Large Firms

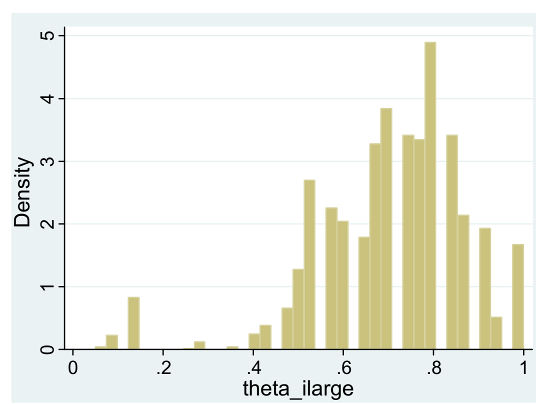
Fig. 3. S&P domestic issuer long term credit rating. In the sample the lowest rating is 1 whereas the highest is 28.



(a) Sample Distribution of Pledgeability Indices



(b) Sample Distribution of Pledgeability Indices – Small Firms



(c) Sample Distribution of Pledgeability Indices – Large Firms

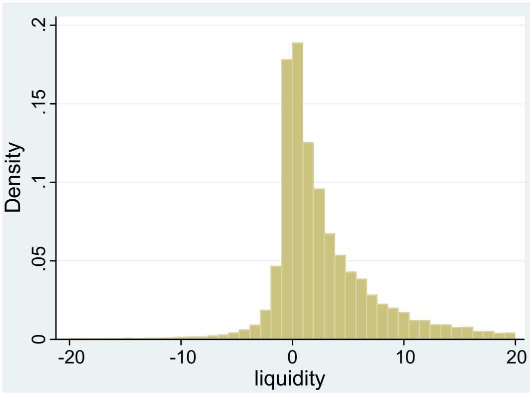
Fig. 4. Firm's pledgeability index is computed by the transformation of long term credit rating observed in the data into an index number between 0 and 1 as discussed in Section 5.

(1) How does the presence of financial pledgeability mitigate the capital rental distortions at the firm level, affect the industry-wide aggregate TFPR and TFPR dispersion, and as a result the industry-wide TFP?
(2) How does the presence of asset liquidity mitigate the capital rental distortions at the firm level, affect the industry-wide aggregate TFPR and TFPR dispersion, and as a result the industry-wide TFP?

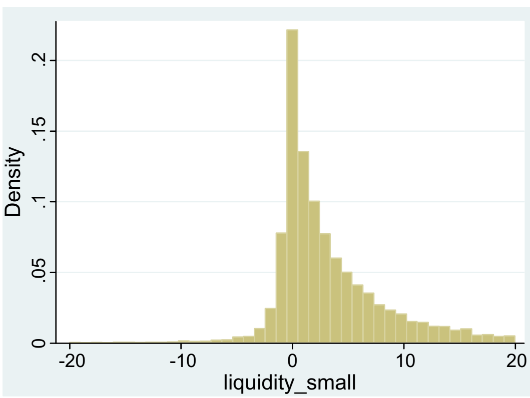
To conduct the first exercise, I hypothetically change the financial pledgeability level for each financially constrained firm to zero. After this hypothetical change each constrained firm faces larger capital market barriers. Basically each firm's capital–labor ratio choice gets distorted by $\hat{\gamma_{si}}$ instead of γ_{si}, where $\gamma_{si} = \tau_{si}(1-\theta_{si})(1-\lambda_{si})$ and $\hat{\gamma_{si}} = \tau_{si}(1-\lambda_{si})$.

Similarly, for the second exercise, I hypothetically change the asset liquidity level of each financially constrained firm to zero. In this case, each constrained firm would face $\tilde{\gamma_{si}}$ instead of γ_{si}, where $\gamma_{si} = \tau_{si}(1-\theta_{si})(1-\lambda_{si})$ and $\tilde{\gamma_{si}} = \tau_{si}(1-\theta_{si})$.

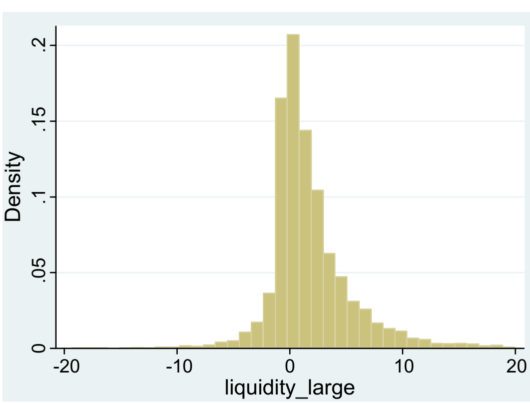
Tables 6 and 7, list for seven major industry clusters, the effects of these hypothetical changes on average capital–labor distortions,



(a) Sample Distribution of Asset Liquidity

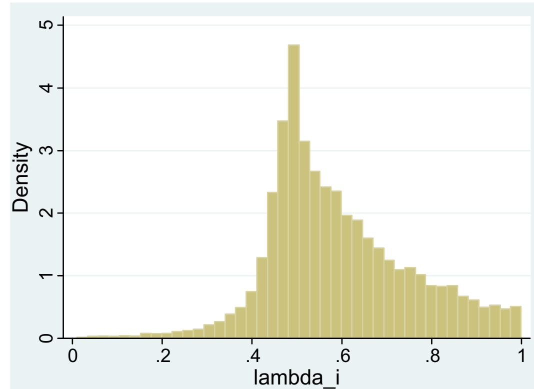


(b) Sample Distribution of Asset Liquidity – Small Firms

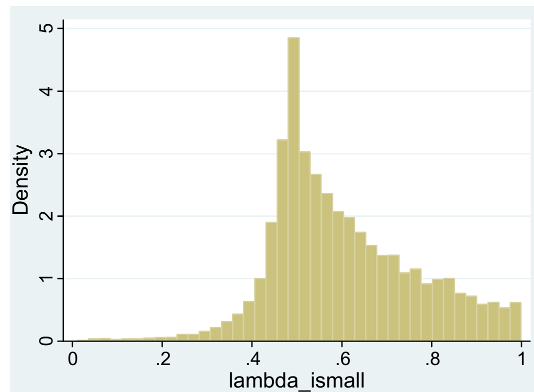


(c) Sample Distribution of Asset Liqudity – Large Firms

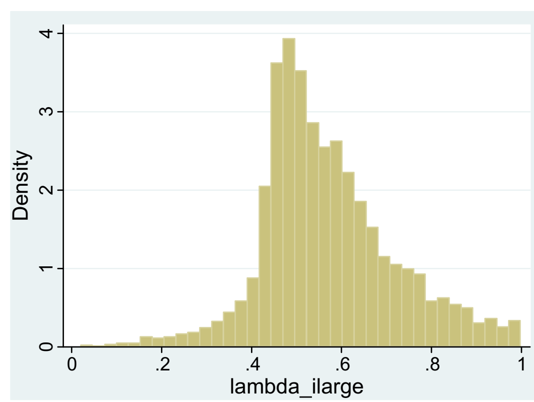
Fig. 5. Asset liquidity is measured as (Current Assets – Current Liabilities)/Current Liabilities.



(a) Sample Distribution of Asset Liquidity Indices



(b) Sample Distribution of Asset Liquidity Indices – Small Firms



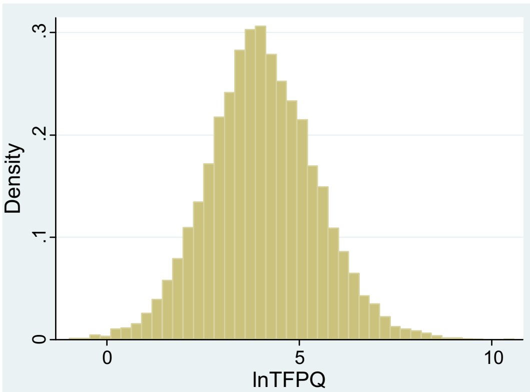
(c) Sample Distribution of Asset Liquidity Indices – Large Firms

Fig. 6. Asset liquidity index is the transformation of asset liquidity observed in the data into an index number between 0 and 1 as discussed in Section 5.

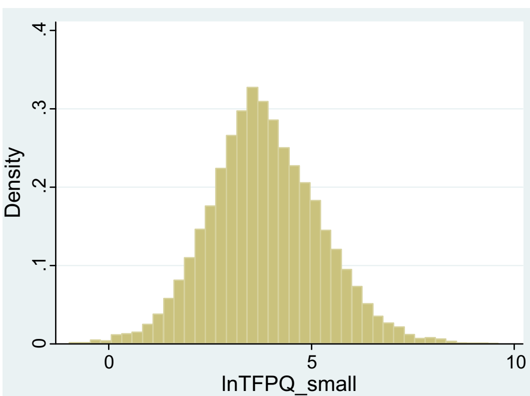
implied TFPR dispersion for each industry, and the resulting aggregate industry TFP.[6]

Both financial pledgeability and asset liquidity are quantitatively important for the industry-wide TFPR dispersion. However, the results show that the mitigating effects of financial pledgeability and asset liquidity on distortions generated by capital rentals are not uniform across different industry clusters. For example, the reduction of financial pledgeability to the lowest possible level in the distribution increases the intra-industry TFPR dispersion by 200% in the IT Sector, by 239% in the Textile and Fabrics Sector and by 116% in the Food and Beverage Sector. In FIRE and Metal–Mineral industry clusters the effects of financial pledgeability are quite substantial as well, as it can be observed in Table 6. The effects of financial pledgeability on intra-industry TFPR dispersion has quantitatively important implications for the aggregate TFPS. The rise in TFPR dispersion in IT, Textiles and Fabrics, and Food and Beverages sectors lead to TFP losses at significant proportions. In IT, the industry TFP decreases by 83%, in Textile Fabrics the TFP decreases by 133%, and finally in Food and Beverages the TFP drops by 47% as we suppress the mitigating effects of firm level financial pledgeability. As I present in Table 6, these numbers mean that the TFP of the IT sector in the data is 1.83 times higher than the TFP following the counterfactual exercise, and the TFP of the Textiles and Fab-

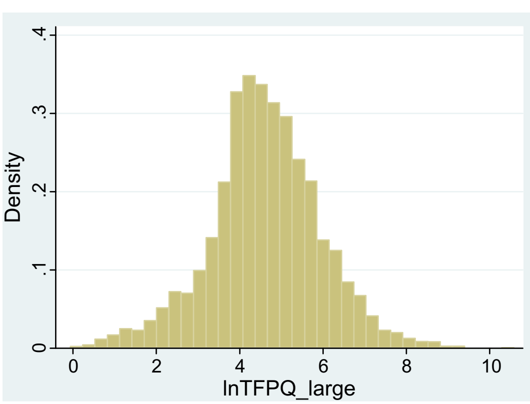
[6] I also study the implications of decreasing both the level of financial pledgeability and the level of asset liquidity to zero for aggregate industry TFP. The results can be found in Table 8.



(a) Sample Distribution of lnTFPQ

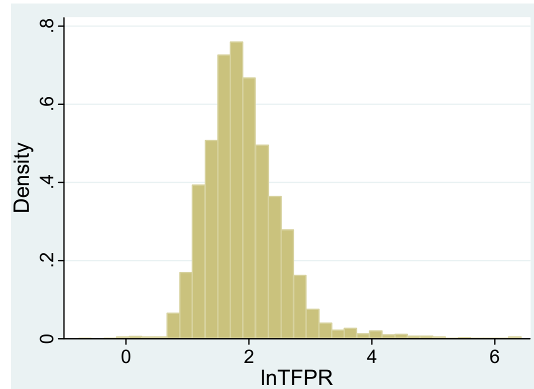


(b) Sample Distribution of lnTFPQ – Small Firms

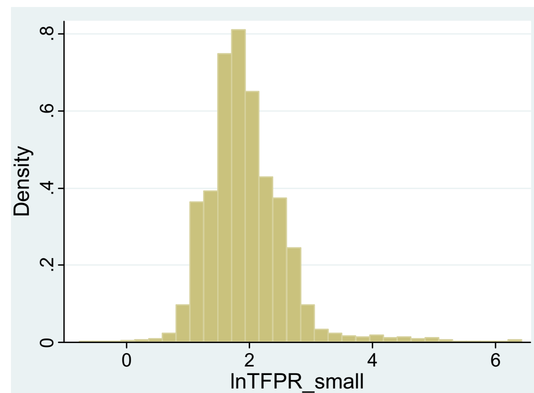


(c) Sample Distribution of lnTFPQ – Large Firms

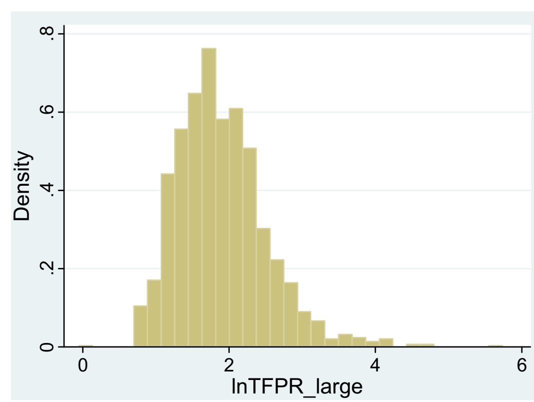
Fig. 7. lnTFPQ is the natural log of firm level total factor productivity quality.



(a) Sample Distribution of lnTFPR



(b) Sample Distribution of lnTFPR – Small Firms



(c) Sample Distribution of lnTFPR – Large Firms

Fig. 8. lnTFPR is the natural log of firm level total factor productivity revenue.

rics sector in the data is 2.33 times higher than the TFP following the counterfactual exercise.

The quantitative analysis shows that the sensitivity of the aggregate industry TFP to firms' ability to borrow against their market pledgeability matter more for industry clusters such as IT and Textiles and Fabrics. In these sectors production output is highly intangible as oppose to sectors such as Chemicals and Petroleum and Transportation Equipment.

Similarly dropping each firm's financial asset liquidity level to zero has quantitatively important implications for the intra-industry TFPR variance as well as for the industry TFP. Suppressing financing against internal assets increases the industry TFPR dispersion for the Chemicals and Petroleum Sector by 455%, for Textiles and Fabrics by 79%, for Food and Beverages by 59%, and for the IT Sector by 48%. As a response to the counterfactual experiment, in the Chemicals and Petroleum industry a large TFP loss of 113% can be accounted for; whereas, in the Textile Fabrics industry the TFP decreases by 75%. The TFP increases by 57% in Minerals and Metalindustry as a response to shutting down the ability to borrow against financial pledgeability. These quantitative results imply that the TFP of the Chemicals and Petroleum sector in the data is 2.13 times higher than the TFP following the counterfactual exercise, and the TFP of the Textiles and Fabrics sector in the data is 1.75 times higher than the TFP following the counterfactual exercise.

The large effects of financial asset liquidity and almost no-effects of financial pledgeability on the TFPR dispersion and aggregate industry performance in Chemicals and Petroleum industry suggests the importance of self financing for this sector and hence

Table 3
Industry productivity and capital rental distortions.

Industry	lnTFPRS	lnTFPS	τ (mean)	τ (st. dev.)
Utilities	2.15	3.07	7.41	5.50
Wholesale trade	2.62	2.26	4.78	6.23
Retail trade	2.53	2.20	5.25	4.64
Warehousing	1.38	1.62	4.27	3.19
Oil and gas	1.59	2.20	1.51	4.10
Minerals and ores	2.30	1.74	2.51	3.88
Food and kindred products	2.60	2.37	7.69	4.04
Beverages and tobacco products	2.66	2.42	4.03	3.60
Textiles and fabrics	1.66	1.13	2.77	0.82
Paper	2.51	1.82	1.69	2.32
Petroleum and coal products manufacturing	2.67	3.10	2.48	3.69
Chemical manufacturing	2.28	2.36	7.39	4.37
Plastics and rubber products manufacturing	1.93	1.70	4.54	2.92
Nonmetalic mineral product manufacturing	2.28	1.90	4.60	3.78
Primary metal manufacturing	2.19	1.80	3.69	2.98
Fabricated metal manufacturing	1.85	1.63	3.76	1.97
Machinery manufacturing	1.81	1.67	2.36	3.00
Computer and electronics manufacturing	1.60	1.39	−0.55	1.27
Electrical equipment and appliances	1.90	1.85	8.93	1.59
Transportation equipment manufacturing	2.12	1.76	3.96	5.82
Air transportation	1.99	1.75	2.34	5.49
Rail transportation	1.43	1.71	2.52	2.49
Water transportation	1.83	2.02	0.20	2.43
Truck transportation	1.87	1.61	9.74	8.11
Publishing industries	2.00	1.84	10.05	5.93
Credit intermediation and related activities	3.02	2.06	4.70	7.21
Security products and related activities	1.75	2.19	3.55	4.77
Insurance carriers and related activities	3.14	2.70	19.75	3.01
Rental and leasing services	2.59	2.07	5.83	3.60
Ambulatory health care services	1.81	1.81	5.66	6.32
Hospitals	1.09	0.94	−0.64	1.14
Nursing and residential care facilities	0.87	0.42	1.76	3.72
Accommodation	1.75	1.45	2.53	3.17
Food services and drinking places	1.82	1.12	6.76	7.17
Accounting and book keeping	1.72	1.41	9.51	1.83
Architectural and engineering services	1.65	1.53	2.34	2.27
Advertising and related services	1.62	1.61	18.61	1.93

TFPRS is the industry aggregate revenue productivity which is calculated using the Eq. (3.17) whereas TFPS is the aggregate industry TFP which is calculated using Eq. (3.19).

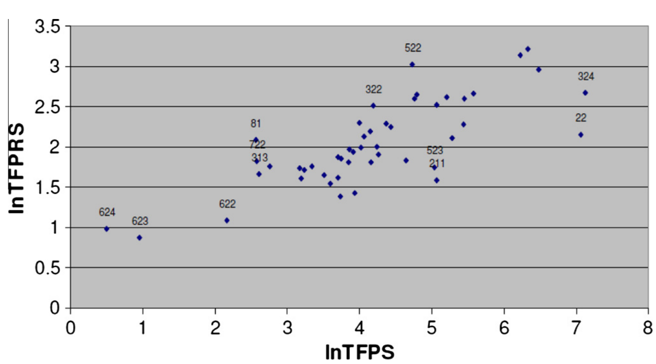


Fig. 9. The correlation between TFPRS and TFPS.

the mitigating effects of financial asset liquidity against distortionary capital rental rates. Shutting down the asset liquidity channel has significant effects for the IT and Textiles and Fabrics industries as does financial pledgeability. Minor effects of pledgeability and liquidity on TFPR dispersion in FIRE industry cluster suggests the presence of a Lucasian ‘‘span of control effect’’ associated with the industries included in FIRE which was not modeled in this current setting.

These key results suggest that the ability to borrow against reputation (pledgeability) as well as against liquid assets matter for capital–labor misallocation in industries with high innovation intensity, such as IT and Textile and Fabrics; whereas, the ability to borrow against liquid assets matters for the observed misallocation and productivity dispersion in industries with relatively lower innovation intensity, such as Chemicals and Petroleum.

4.2. Intra-industry misallocation and financial structure of firms

The quantitative results from this paper indicate that the financial structure of financially constrained firms is important for allowing productive entrepreneurs to acquire investable funds and mitigating the misallocation inefficiency within a sector of firms. Banerjee and Moll (2010) pointed out that focusing on firms' finance would be consistent with Hsieh–Klenow's framework, since in Hsieh–Klenow's quantitative analysis most of the TFP losses in India and China (two case studies Hsieh and Klenow (2009) take into consideration) are generated by the inefficient distribution of capital across producers. Therefore, different from the Hsieh and Klenow (2009), the results from this paper provide an understanding for the potential sources of total factor productivity gains that could result from lowering financial distortions.

In identifying the aggregate implications of firms' financial access dispersion, I utilize detailed balance sheet information from major US industry clusters. Focusing on a single country's sectoral differences, when studying firm balance sheet data, has an important advantage over a cross-country analysis. The distribution of financial characteristics within a sector can exhibit country specific characteristics. In this respect, an important issue is related to the complementarity between labor skills and firms' capital use. For example, Acemoglu and Zilibotti (2001) show that firms in low income countries might be inherently less capital intensive which in

Table 4
Productivity and capital rental distortions, pledegability and asset liquidity.

Sector	# Of firms	τ (mean)	τ (s.d.)	Pledgeability	Liquidity
IT	105	27. 19	58.83	0.62	0.75
FIRE	113	452.49	1855.48	0.74	0.61
Food and beverages	34	60.65	116.43	0.68	0.58
Textiles and fabrics	52	30.23	24.47	0.57	0.71
Chem. and petroleum	65	77.90	386.31	0.72	0.65
Metal and mineral	32	64.06	209.97	0.60	0.64
Transportation equip.	17	36.76	93.70	0.65	0.63

IT stands for Information Technology whereas FIRE stands for Finance–Insurance–Retail Trade-and-Real Estate. Capital distortions are computed using observed K/L distortions and the observed financial pledgeability and observed asset liquidity.

Table 5
K/L distortions and TFPRS.

Sector	K/L dist. (mean)	K/L dist. (s.d.)	TFPRS (mean)	TFPRS (s.d.)
IT	1.33	1.72	6.08	1.20
FIRE	9.12	46.41	14.94	23.65
Food and beverages	3.11	2.12	13.42	5.48
Textiles and fabrics	1.56	0.61	5.28	0.38
Chem. and petroleum	3.53	10.72	11.71	15.89
Metal and mineral	2.16	2.45	9.09	7.04
Transportation equip.	1.48	3.43	8.35	3.70

TFPRS is computed using Eq. (3.17).

Table 6
Counterfactual experiment 1: Decreasing the level of financial pledgeability to zero.

Sector	Hypothetical TFPRS (mean)	Hypothetical TFPRS (s.d.)	% Change in TFPRS (s.d.)	% TFPS losses	$\frac{TFP_{data}}{TFP_{hypo}}$
IT	7.98	3.59	200	83	1.83
FIRE	20.85	29.14	23	21	1.21
Food and beverages	19.48	11.85	116	47	1.47
Textiles and fabrics	7.04	1.29	239	133	2.33
Chem. and petroleum	17.74	13.40	−15	−8	0.92
Metal and mineral	12.84	10.28	46	34	1.34
Transportation equip.	8.63	4.04	9	7	1.07

TFPS loss is computed using Eq. (3.19). In this exercise pledgeability is hypothetically decreased to the lowest possible level in the set for all firms.

Table 7
Counterfactual experiment 2: Decreasing the level of asset liquidity to zero.

Sector	Hypothetical TFPRS (mean)	Hypothetical TFPRS (s.d.)	% Change in TFPRS (s.d.)	% TFPS losses	$\frac{TFP_{data}}{TFP_{hypo}}$
IT	7.39	1.78	48	62	1.62
FIRE	21.20	32.48	37	29	1.29
Food and beverages	28.76	8.70	59	22	1.22
Textiles and fabrics	6.81	0.68	79	75	1.75
Chem. and petroleum	30.85	88.22	455	113	2.13
Metal and mineral	10.33	4.028	−43	−57	0.43
Transportation equip.	9.69	4.21	14	10	1.10

In this exercise liquidity is hypothetically decreased to the lowest possible level in the set for all firms.

Table 8
Counterfactual experiment 3: Decreasing pledgeability and liquidity to zero.

Sector	Hypothetical TFPRS (mean)	Hypothetical TFPRS (s.d.)	% Change in TFPRS (s.d.)	% TFPS losses	$\frac{TFP_{data}}{TFP_{hypo}}$
IT	6.51	4.05	238	94	1.94
FIRE	23.19	37.83	60	46	1.46
Food and beverages	32.11	14.19	159	61	1.61
Textiles and fabrics	6.92	1.53	302	158	2.58
Chem. and petroleum	34.21	65.93	315	103	2.03
Metal and mineral	13.59	6.78	−7	−5	0.95
Transportation equip.	11.21	4.30	16	13	1.13

In this exercise pledgeability and liquidity are hypothetically decreased to the lowest possible level in the set for all firms.

turn can generate cross-country differences in the distribution of firm financial structure. Therefore, studying counterfactuals across countries concerning the financial structure dispersion could have drawbacks. By focusing sectoral financial structure differences the current framework avoids such methodological limitations which are prevalent in Hsieh and Klenow (2009).

This paper and as well as Hsieh and Klenow (2009) argue that the distortionary capital rental rates can lead to the misallocation of capital across producers and generate labor intensive production units which can be important in explaining the intra-industry productivity dispersion and industry total factor productivity. To the end of labor intensive production and financing constraints, Garmaise (2008) presents empirical evidence that financially constrained firms operate relatively more labor intensive production units. However, one key assumption which could still be a threat for the identification of the quantitative results of this paper and Hsieh and Klenow (2009) is the "restricted mobility of labor" assumption. Specifically, the misallocation of capital can be partially undone if labor is allowed to be mobile across countries in the Hsieh–Klenow framework, and a similar counteracting effect would emerge if labor could easily switch jobs from a low-TFP sector to a high TFP sector in the framework of this paper. Cross-country labor mobility is substantially low accounting for large cross-country wage differences, as documented in labor economics literature. This cross-country empirical observation supports Hsieh–Klenow's identification assumption.

There is empirical evidence for low labor market mobility across sectors as well: For example, Lee and Wolpin (2006) estimate large costs of labor mobility for switching jobs across broadly defined sectoral clusters for the US economy. Their labor mobility estimates imply that the output in both service and manufacturing sectors would have been double their current levels if these mobility costs had been zero. Furthermore, Lee and Wolpin (2006) also show that the cost of moving between sectors within the same occupation is estimated to be significantly larger than moving between occupations within the same sector. Inter-industry immobility of labor is heavily discussed in international trade literature as well. For example, Wacziarg and Wallack (2001, 2004) and Muendler (2010) document empirical evidence for non-negligible inter-industry flows of labor following trade liberalization experiences in developing countries. The empirical evidence concerning the inter-sectoral mobility of labor argues for large frictions to switching jobs in-between sectors, which supports the key assumption underlying the theoretical model of this paper.

5. Conclusion

This paper studies the sensitivity of production input distortions at the firm level with respect to firm financial characteristics and the implications of this sensitivity for industry-wide firm productivity dispersion and aggregate industry TFP. Basically, in this paper I have studied the effects of financial pledgeability and asset liquidity on capital–labor choice when there are capital market distortions, in terms of heterogeneity in capital rental rates.

The analytical results show that financial pledgeability and asset liquidity can mitigate the effects of distortionary capital rental rates for financially constrained firms. Empirical findings show that the mitigating effect of financial pledgeability on capital–labor ratio distortions is relatively high for small firms, whereas asset liquidity is important for all firm-size classes.

Finally the quantitative analysis shows that the ability to borrow against financial pledgeability and financial asset liquidity matter for intra-industry TFPR dispersion and aggregate industry TFP. However, the type of financial characteristic that has a stronger effect on aggregate industry performance differs across sectors. Therefore, the policy implications suggest that financial development matters for the aggregate productivity, but how the financial markets should be induced to develop is sensitive to sector specific characteristics.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbankfin.2013.11.011.

References

Acemoglu, Daron, Zilibotti, Fabrizio, 2001. Productivity differences. Quarterly Journal of Economics 116 (2).
Antunes, Antonio, Cavalcanti, Tiago, Villamil, Anne, 2008. The effect of financial repression and enforcement on entrepreneurship and economic development. Journal of Monetary Economics 55.
Banerjee, Abhijit, Duflo, Esther, 2005. Growth Theory through the Lens of Development Economics. Elsevier B.V., pp. 473–552.
Banerjee, Abhijit, Moll, Benjamin, 2010. Why does misallocation persist? American Economic Journal: Macroeconomics 2 (1).
Buera, Francisco, Shin, Yongseok, 2013. Financial frictions and the persistence of history: a quantitative exploration. Journal of Political Economy.
Chirinko, Robert, Meyer, Andrew, Fazzari, Steven, 2007. That elusive elasticity: A long panel approach to estimating the price sensitivity of business capital. Journal of Business and Economics Statistics 29.
Eugene, Fama, French, Kenneth, 2002. Testing trade-off and pecking order predictions about dividends and debt. Review of Financial Studies 15 (1).
Foster, Lucia, Haltiwanger, John, Syerson, Chad, 2008. Reallocation, firm turnover, and efficiency: selection and productivity or profitability? American Economic Review 98, 394–425.
Frank, Murray, Goyal, Vidhan, 2003. Testing the pecking order theory of capital structure. Journal of Financial Economics 67.
Garmaise, Mark J., 2008. Production in entrepreneurial firms: the effects of financial constraints on labor and capital. Review of Financial Studies 21 (2).
Hsieh, Chang-Tai, Klenow, Peter, 2009. Misallocation and manufacturing TFP in China and India. Quarterly Journal of Economics 124 (4).
Lee, D., Wolpin, Kenneth, 2006. Intersectoral labor mobility and the growth of the service sector. Econometrica 74 (1).
Matsuyama, Kiminori, 2007. Credit traps and credit cycles. American Economic Review 97.
Midrigan, Virgiliu, Xu, Daniel Yi, 2013. Finance and misallocation: evidence from plant-level data. American Economic Review, forthcoming.
Modigliani, Franco, Miller, Merton, 1958. The cost of capital, corporation finance and the theory of investment. American Economic Review 48 (3).
Muendler, Marc-Andreas, 2010. Trade reform, employment allocation and worker flows. In: Porto, G., Hoekman, B. (Eds.).
Pratap, Sangeeta, Urrutia, Carlos, 2011. Financial frictions and total factor productivity: Accounting for the real effects of financial crises. Review of Economic Dynamics 15 (3).
Rajan, Raghuram G., Zingales, Luiggi, 1998. Financial dependence and growth. The American Economic Review 88.
Restuccia, Diego, Rogerson, Richard, 2008. Policy distortions and aggregate productivity with heterogeneous plants. Review of Economic Dynamics 11 (4), 707–720.
Sandleris, Guido, Wright, Mark, 2011. The Costs of Financial Crises: Resource Misallocation, Productivity and Welfare in the 2001 Argentine Crisis. NBER Working Paper, No: 17552.
Wacziarg, Romain, Wallack, Jessica S., 2001. Trade Liberalization and Intersectoral Labor Movements. Working paper, Stanford Graduate School of Business, October.
Wacziarg, Romain, Wallack, Jessica S., 2004. Trade liberalization and intersectoral labour movements. Journal of International Economics 64.