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CREDIT CONDITIONS, DYNAMIC DISTORTIONS, AND CAPITAL ACCUMULATION IN MEXICAN MANUFACTURING

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Credit Conditions, Dynamic Distortions, and Capital Accumulation in Mexican Manufacturing*

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Abstract

The objective of this paper is to document a transmission channel from credit conditions to capital accumulation at a disaggregated level. We use a simple multi-sector model of production and investment to identify investment wedges (i.e., deviations from the optimality condition implied by a stochastic Euler equation). Using a panel of observations at the 4-digit level from the Mexican manufacturing industry, we measure the corresponding dynamic distortions in capital accumulation. Our counterfactual experiments show that the behavior of capital distortions is important to account for changes in the aggregate capital stock over time. We then analyze the sources of these distortions, working with one important candidate: bank credit. We show in a simple model of investment with financial frictions that more availability and cheaper access to credit reduce capital distortions. We find some statistical support for this mechanism in the data.

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1 Introduction

Capital accumulation is an important driver of economic growth. At the same time, investment is highly volatile and responsive to the business cycle. The objective of this paper is to analyze the impact of bank credit on firms' investment decisions and on aggregate capital accumulation. Our analysis uses a rich sectoral structure within Mexican manufacturing and exploits changes observed during a ten year period. The transmission channel that we explore links credit conditions and sectoral distortions (i.e., deviations from the optimal allocation of resources across sectors and over time), in particular the dynamic capital distortion.¹

This analysis complements our results from a companion paper (Meza, Pratap and Urrutia 2016), where we consider the impact of banking credit on static distortions and total factor productivity (TFP). In both projects, we study distortions that are heterogeneous across sectors, focusing on their evolution over time more than in their absolute size. The main message from our previous work is that changes in the cost and availability of credit can account for a large extent of the observed changes in aggregate TFP in Mexican manufacturing industry through their impact on static distortions. Moreover, heterogeneity across sectors in the changes in credit conditions is key for their impact on the misallocation of resources.

In this paper, we extend the transmission mechanism to dynamic distortions and assess its importance in explaining capital accumulation.² For this, we use a simple multi-sector model of production and investment that allows us to identify both static and dynamic wedges. We measure the corresponding labor and capital distortions using microdata for the Mexican manufacturing industry and use the model to assess how important these distortions are in accounting for the behavior of the capital stock and TFP. We also estimate how these distortions are related to the sector-specific credit intensities and interest rates. To the best of our knowledge, this is one of the first papers measuring heterogenous capital distortions and providing an economic content to their evolution over time.³

An older literature on the effects of financial constraints on firm investment uses both reduced form estimates (see Hubbard 1997 for a survey) and structural techniques (Pratap and Rendon 2003, Hennessey and Whited 2007). These papers however do not measure the capital distortions directly, and do not consider the aggregate implications of the effects they estimate. More recent work by Gopinath et al. (2017) and Bai et al. (2017) study the effects of financial frictions on capital misallocation in Southern Europe and China respectively. These studies however, do not have detailed financial information on heterogeneous credit conditions and focus on the dispersion of the marginal product of capital.

¹Given technology and endowments, we can define the optimal allocation of resources across firms and over time within a theoretical framework. The optimal allocation is usually characterized by a set of static first order conditions on input purchases and a dynamic and stochastic Euler equation on capital accumulation. A wedge appears whenever firms deviate from this optimal choice. The literature uses implicit taxes or distortions to describe all factors behind these wedges in a compact way (see Restuccia and Rogerson 2008), but the main challenge is to provide some economic content to them.

²Starting with the work of Hsieh and Klenow (2009) there is a growing body of research on the measurement of static heterogenous distortions on input use across establishments, firms, or sectors of different countries. Additionally, there has been some work on the origin of these distortions (see Hopenhayn (2014) for a comprehensive survey and Busso, Fazio and Levy (2012) for an analysis of the role of the informal sector in Mexico). Most of this research looks at the impact of static distortions on the level of macroeconomic variables, not on their evolution over time. A few exceptions include the work of Chen and Irarrazabal (2015), Sandleris and Wright (2014) and Gopinath et al. (2017) for the cases of Chile, Argentina and Southern Europe, respectively.

³The heterogeneity in capital distortions is important since, as Buera and Moll (2015) show, the aggregate investment wedge can be uninformative about the presence of heterogeneous distortions driven by financial frictions.

Our empirical analysis is based on the merged dataset that we built in Meza, Pratap and Urrutia (2016), linking output, employment and investment with credit flows and interest rates at the 4-digit sector level for the Mexican manufacturing industry. The data on real activity come from the annual industrial survey (EIA for its acronym in Spanish) collected by the Mexican statistical agency INEGI. The financial information comes from the R04C credit registry maintained by the banking regulatory authority, the *Comisión Nacional Bancaria y de Valores*. Due to confidentiality restrictions we work at the 4-digit industry level, following the 2007 North American Industrial Classification System (NAICS). This gives us a panel of 82 manufacturing sectors for 11 years, from 2003 to 2013.

An important contribution of the paper is the measurement of the investment wedge using sectoral data.⁴ Our procedure exploits the panel nature of our data. We use the policy function for capital to estimate the parameters of the unobserved process for the capital distortion, using an iterative procedure. In addition, the labor distortion is simply backed out from a static decision using data on sectoral labor allocation.

The two main results of the paper are as follows. First, we show that changes in the sectoral capital distortions are important in accounting for the fluctuations in the speed of capital accumulation over time. Even though aggregate TFP stagnates between 2006 and 2009, capital accumulation accelerates in this period and this is associated with a reduction in the average investment wedge. The reverse is true for 2009-2012; capital accumulation slows down, despite a rise in aggregate TFP, consistent with the observed increase in the average capital distortion.

Second, we find a robust link between the observed changes in the capital distortion for each sector and the respective, sector-specific, credit conditions. Sectors for which credit availability decreases and/or real interest rates increase experience, on average, an increase in their capital distortions. This result, which we rationalize with a simple model of investment with financial frictions, is robust to the introduction of both time and fixed effects in a panel regression and highlights the importance of the banking system in financing working capital and investment in the Mexican manufacturing sector. Together, the two results extend the transmission channel from credit to real activity analyzed in Meza, Pratap and Urrutia (2016) to a dynamic setup.

The outline of the paper is as follows. In Section 2 we describe a simple model of production and investment decisions in a multi-sector economy, where labor and capital distortions generate sub-optimal allocations. Section 3 describes how we measure these distortions in our dataset. In Section 4 we carry out counterfactual experiments to analyze the contribution of each type of distortion to changes in the aggregate capital stock and TFP. In Section 5 we investigate the link between the measured distortions and credit conditions faced by each sector, i.e. the amount and cost of credit. Finally, we conclude.

⁴The measurement of the capital distortion at an aggregate level has been done, among others, by Chari, Kehoe and McGrattan (2007). They use time series of macroeconomic variables for the United States, which they combine with a policy function from the neoclassical model to back out the aggregate investment wedge. A similar approach is followed in Lama (2011) using aggregate data for emerging economies, including Mexico. A more disaggregated approach, such as ours, has the advantage of allowing us to measure the effects of heterogeneity on the aggregate economy.

2 A Production and Investment Model with Sector-Specific Distortions

Consider a simple model of production with multiple sectors, each of which is characterized by a representative firm operating in a perfectly competitive market, using a constant returns to scale production technology. Firms produce output using capital and labor. They own the capital stock and make investment decisions in an uncertain environment. In addition, they face sector specific distortions that we model as a static labor wedge and a dynamic investment wedge, which we take for now as primitives.

2.1 The Model Economy

The production structure of the model consists of n sectors, each of which is characterized by a representative firm, operating under constant returns to scale and perfect competition. In each period, firms produce output using capital and labor according to the Cobb-Douglas production function

$$Y_t^i = A_t^i (K_t^i)^{\alpha^i} (L_t^i)^{1-\alpha^i} \quad i \in \{1, \dots, n\}. \quad (1)$$

Firms own their capital stock and take prices as given. The representative firm in each sector maximizes the expected present value of the stream of profits net of investment expenditures

$$\Pi^i \equiv E_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+\iota} \right)^t \left\{ p_t^i Y_t^i - \theta_t^{L,i} w_t L_t^i - \theta_t^{K,i} [K_{t+1}^i - (1-\delta) K_t^i] \right\},$$

where $\theta_t^{L,i}$ and $\theta_t^{K,i}$ are sector specific distortions that affects the cost of the labor input and the cost of investment.⁵ The expectation is taken over future values of revenue productivity and both labor and capital distortions. We assume for now that firms can borrow or lend at the constant, risk free rate ι .

The solution of this maximization problem satisfies the first order condition for labor

$$\theta_t^{L,i} w_t L_t^i = (1 - \alpha^i) p_t^i Y_t^i$$

and the stochastic Euler equation

$$\theta_t^{K,i} = \frac{1}{1+\iota} E_t \left\{ MRK_{t+1}^i + (1-\delta) \theta_{t+1}^{K,i} \right\},$$

where the marginal revenue of capital in each period can be written as

$$MRK_t^i = \alpha^i p_t^i A_t^i (K_t^i / L_t^i)^{1-\alpha^i}$$

a function of the capital to labor ratio.

⁵In the Appendix we discuss an extension with intermediate goods and a static distortion affecting the use of intermediates. Our previous work (Meza, Pratap and Urrutia (2016)), indicates that this margin is important to understand misallocation and aggregate TFP in a static framework. It turns out that its impact on capital accumulation is small.

2.2 Obtaining the Sectoral Labor Allocation

We assume that the output of each sector is combined using a Cobb-Douglas aggregator to produce aggregate output

$$Y_t = \prod_{i=1}^n (Y_t^i)^{\omega^i}. \quad (2)$$

This aggregator implies that the expenditure shares in each sector are constant and equal to ω^i . We can then write the static first order condition for labor as

$$L_t^i = \left(\frac{1 - \alpha^i}{\theta_t^{L,i}} \right) \omega^i \frac{Y_t}{w_t},$$

normalizing the price of the final good to one.

Aggregating labor across sectors, we obtain

$$L_t = \sum_{i=1}^n L_t^i = \Phi \frac{Y_t}{w_t},$$

with the aggregate labor share defined as $\Phi_t \equiv \sum_{j=1}^n \frac{\omega^j (1 - \alpha^j)}{\theta_t^{L,j}}$. It follows that

$$L_t^i = \left(\frac{\omega^i (1 - \alpha^i)}{\Phi_t \theta_t^{L,i}} \right) L_t, \quad (3)$$

so the aggregate labor input, that we take as exogenous, is allocated across sectors based on technological parameters and static distortions only. A sector with a larger share in total expenditures (ω^i), higher labor intensity in production (lower α^i) and/or a smaller distortion to labor ($\theta_t^{L,i}$) uses a larger fraction of the labor input.

We perform now two further normalizations. First, we assume that the aggregate labor input L_t is constant and equal to one, so all variables are expressed in per worker terms. Also, we assume that the labor distortions cancel out on average, since what matters is their dispersion. In other words, we normalize $\Phi_t = 1 - \alpha$, with $\alpha \equiv \sum_{j=1}^n \omega^j \alpha^j$, so that all labor distortions should be interpreted as relative to the (weighted) average aggregate distortion.

2.3 Solving the Linearized Euler Equation

Under these assumptions, substituting (3) in the Euler equation, we get a stochastic difference equation in the capital distortion $\theta_t^{K,i}$ where

$$\theta_t^{K,i} = \frac{1}{1 + \iota} E_t \left\{ \alpha^i p_t^i A_t^i \left(\frac{\omega^i (1 - \alpha^i)}{(1 - \alpha) \theta_t^{L,i} K_t^i} \right)^{1 - \alpha^i} + (1 - \delta) \theta_{t+1}^{K,i} \right\}. \quad (4)$$

This equation allows us to compute the long run value of capital in the deterministic steady state

$$\overline{K^i} = \left(\frac{\alpha^i \overline{p^i A^i}}{\overline{\theta^{K,i}} (\iota + \delta)} \right)^{\frac{1}{1 - \alpha^i}} \left(\frac{\omega^i (1 - \alpha^i)}{(1 - \alpha) \overline{\theta^{L,i}}} \right). \quad (5)$$

In what follows, we work with the log-linearized version of the Euler equation around this deterministic steady state.

Defining $\widetilde{x}_t \equiv \log(x_t) - \log(\bar{x})$ and using the steady state capital condition (5), we can approximate the Euler equation in log-deviations by:

$$\widetilde{\theta}_t^{K,i} = \frac{1}{1+\iota} \left\{ (\iota + \delta) E_t \left[p_{t+1}^i \widetilde{A}_{t+1}^i - (1 - \alpha^i) \left(\widetilde{K}_{t+1}^i + \widetilde{\theta}_{t+1}^{L,i} \right) \right] + (1 - \delta) E_t \widetilde{\theta}_{t+1}^{K,i} \right\}.$$

Furthermore, assuming that (the log of) revenue productivity and the two distortions follow AR(1) stochastic processes with persistences ρ_A , ρ_L , ρ_K , we can write the linearized Euler equation as

$$\Psi \widetilde{\theta}_t^{K,i} = \rho_A p_t^i \widetilde{A}_t^i - (1 - \alpha^i) \widetilde{K}_{t+1}^i - (1 - \alpha^i) \rho_L \widetilde{\theta}_t^{L,i} \quad (6)$$

with $\Psi \equiv \frac{(1+\iota)-(1-\delta)\rho_K}{\iota+\delta}$.⁶

To solve for the optimal decision rule, we postulate a linear policy function mapping capital tomorrow to the state variables of the firm:

$$(1 - \alpha^i) \widetilde{K}_{t+1}^i = \gamma \widetilde{K}_t^i + \gamma_A p_t^i \widetilde{A}_t^i + \gamma_K \widetilde{\theta}_t^{K,i} + \gamma_L \widetilde{\theta}_t^{L,i}. \quad (7)$$

Replacing in (6) and solving, we obtain

$$\gamma \widetilde{K}_t^i + (\gamma_A - \rho_A) p_t^i \widetilde{A}_t^i + (\gamma_K + \Psi) \widetilde{\theta}_t^{K,i} + [\gamma_L + (1 - \alpha^i) \rho_L] \widetilde{\theta}_t^{L,i} = 0$$

admitting the solution $\gamma = 0$, $\gamma_A = \rho_A$, $\gamma_K = -\Psi$ and $\gamma_L = -(1 - \alpha^i) \rho_L$.

2.4 Aggregating Capital, Output and TFP

The policy function (7) allows us to construct a sequence of capital stock for given sequences of revenue productivity and distortions for each sector. Adding up across sectors, we can get the aggregate capital stock. Using the production function (1) for each sector and the static labor allocation (3),

$$Y_t = \sum_{i=1}^n p_t^i A_t^i (K_t^i)^{\alpha^i} \left(\frac{\omega^i (1 - \alpha^i)}{(1 - \alpha) \theta_t^{L,i}} \right)^{1 - \alpha^i}$$

we obtain a measure of aggregate output depending only on the sectoral capital allocation, sectoral revenue productivities, the static labor distortions and technology parameters. Notice again that, because of our normalization of the total labor input, aggregate capital and aggregate output are expressed in per worker terms. Finally, we define aggregate measured TFP as the ratio Y_t / K_t^α .

⁶Notice that the persistences of these shocks are assumed to be common across sectors, while their long run values are sector specific. Also, since the data do not allow us to separate sector specific prices from output and productivity, we model revenue productivity as a single shock.

3 Measuring Sectoral Distortions

Using the framework from the previous section we perform now the inverse exercise: Given the observed revenue productivities, labor allocation and sectoral capital sequences, we recover the wedges that are consistent with these observations in the model. For this, we use microdata on real activity for the Mexican manufacturing sector obtained from the annual industrial survey (EIA for its acronym in Spanish). We discuss the statistical properties of these wedges at the end of this section.

3.1 Data on Real Activity

We measure the capital and labor sectoral distortions using annual data from the Mexican industrial manufacturing survey (EIA) from 2003 to 2013. The data is aggregated to the 4-digit NAICS classification. Once we exclude sectors with missing information and one clear outlier (Oil products and derivatives), we have a total of 82 sectors within manufacturing (so $n = 82$ in the model).

For each sector, we use data on gross output and expenditure on intermediate goods to construct measures of value added. We define sectoral investment as the sum of all purchases of investment goods, including structures and equipment. Both value added and investment are deflated by the manufacturing PPI index to obtain real sectoral revenue and real investment. The capital input is constructed using the perpetual inventory method: We use a steady-state assumption to calculate the initial capital stock in each sector, and then update it over time using investment flows and the average depreciation rate ($\delta \approx 0.08$). The labor input is measured as the number of people hired directly and indirectly by all firms.

3.1.1 Estimation of the Productivity Process

Obtaining the capital share in each sector from the EIA data is a difficult task, since the corresponding expenditure share is already affected by distortions.⁷ Following Hsieh and Klenow (2009), we use the capital share from the corresponding sectors in the U.S. for 2003, as an example of an undistorted economy.⁸ Using these shares and the data on sectoral revenue and inputs, we compute revenue productivity in each sector and year from the production function as

$$p_t^i A_t^i = \frac{p_t^i Y_t^i}{(K_t^i)^{\alpha^i} (L_t^i)^{1-\alpha^i}}$$

and estimate a dynamic panel regression using the Arellano-Bond method. The estimation delivers, among other results, a long run value $\overline{p^i A^i}$ for each sector and a persistence parameter $\rho_A \approx 0.38$.

3.2 Recovering the Sectoral Wedges

With this information, we can compute the implied capital and labor distortions in the model. First, we obtain the static labor wedge from the condition (3), using the observed labor allocation sequences. We also compute a panel for the investment wedges from the linearized Euler equation (6), substituting the observed

⁷We discuss this identification problem in some detail in our previous paper Meza, Pratap and Urrutia (2016).

⁸The shares ω^i are just computed from the EIA dataset as the value added generated by sector i relative to the total value added in manufacturing.

| | 2003-05 | 2005-08 | 2008-09 | 2009-12 |
|---|---------|---------|---------|---------|
| Capital Distortion ($\theta_t^{K,i}$) | | | | |
| - Mean | 6.41 | 6.34 | 6.25 | 6.35 |
| - C.V. (std deviation/mean) | 0.60 | 0.59 | 0.60 | 0.60 |
| - Correlation with Employment (L_t^i) | -0.03 | -0.03 | -0.01 | -0.03 |
| - Correlation with Productivity ($p_t^i A_t^i$) | 0.19 | 0.12 | 0.14 | 0.16 |
| Labor Distortion ($\theta_t^{L,i}$) | | | | |
| - Mean | 1.00 | 1.00 | 1.00 | 1.00 |
| - C.V. (std deviation/mean) | 1.17 | 1.19 | 1.18 | 1.19 |
| - Correlation with Employment (L_t^i) | 0.00 | -0.00 | -0.01 | -0.02 |
| - Correlation with Productivity ($p_t^i A_t^i$) | 0.59 | 0.56 | 0.57 | 0.50 |
| Correlation between distortions | 0.55 | 0.57 | 0.56 | 0.57 |

Table 1: Descriptive Statistics for the Capital and Labor Distortions

sectoral revenue productivities, labor distortions and capital sequences. Notice that because of its dynamic nature we lose one observation, so the resulting panel of distortions only covers the period 2003-12.⁹

Table 1 reports some summary statistics for these panels of distortions. The statistics are computed in each year for the cross-section of sectors and averaged within four subperiods: The first two periods are both periods of growth in output, the first accompanied by credit stagnation and the second by credit growth. The third period is the Great Recession of 2008-09 and the last subperiod is the recovery from the financial crisis. Notice that the average capital distortion is quite high and changes over these periods (we will come back to these changes in the next subsection). In contrast, by construction the average labor distortion is constant and equal to one, but its dispersion across sectors is higher. Both distortions are essentially uncorrelated with size (measured by the share of employment), but positively correlated with revenue productivity. This suggests that the removal of the distortions would potentially have large effects on output and investment by allowing these sectors to expand.

The distribution of distortions across the 82 sectors are shown in Figures 1 and 2. A value of 1 implies an absence of distortions. Notice that there are almost no sectors with undistorted investment. The distribution is skewed to the right, and many sectors are substantially distorted. The labor distortion in contrast, is relatively smaller and less dispersed.

⁹The computation of the investment wedge requires a value for the persistence of the distortions, ρ_K and ρ_L . The persistence of the labor wedge ρ_L is estimated from the labor wedge series, using the Arellano-Bond estimator. This also gives us the long run values of the wedge for each sector. For the parameters of the investment wedge, we follow an iterative procedure: Starting from an initial guess for ρ_K , and the sector specific long run values of the investment wedge, we compute the implied investment wedges using (6) for each sector and year. We update our estimates of the persistence and steady states using the Arellano-Bond estimator. These updated values are plugged into the Euler equation again, to give us a new series on the capital distortion. We repeat this process till the estimates converge. This delivers a persistence of $\rho_K \approx 0.69$, $\rho_L \approx 0.73$, and vectors of long run values.

4 Distortions and Capital Accumulation

Using the panels of distortions obtained in the previous section we can back out the allocations in the baseline economy. Starting from the observed initial capital stock in each sector, we iterate on the policy rule (7) to construct sequences of capital for the 10-year period 2003-12. Also, using (3), we obtain a similar panel for labor, so sectoral output can be computed from the individual production function (1). Finally, we aggregate output and the capital stock and compute aggregate TFP as described before. By construction, these allocations from the baseline model exactly match their empirical counterparts. Starting from this benchmark, we perform a set of counterfactual experiments to measure the contribution of changes in each distortion to the evolution of aggregate capital and TFP.

4.1 Dynamic Distortions, TFP and Capital Accumulation

Figure 3 plots the evolution of the average capital distortions, averaged across all sectors, and compares it to the evolution of the aggregate capital stock (per worker) and TFP in the baseline economy. As expected, average capital distortions are inversely related to aggregate capital. In particular, a reduction in the investment wedge between 2006-08 is associated to an increase in the speed of capital accumulation, while the opposite is observed in 2009-12. These two episodes do not seem to be consistent with an explanation of investment based on its technological profitability only: In the expansion period before the crisis aggregate TFP stagnates, while in the years following the crisis TFP recovers but capital accumulation does not.

To further explore these movements in capital and TFP, the first counterfactual experiment keeps the capital distortion constant at its long run value for each sector throughout the whole period. In this alternative scenario, we recompute the allocations in the model, in particular aggregate capital and TFP, and compare them in Figure 4 to the baseline economy. Now capital accumulation and TFP move in the same direction. In contrast to the benchmark model, we observe a slowdown in capital accumulation before the crisis and an increase in investment after the crisis. This confirms the importance of dynamic capital distortions in shaping the incentives to invest and determining the rate of capital accumulation.

4.2 Static Distortions and Capital Accumulation

In the experiment reported in Figure 5 we keep both the capital and the labor distortions constant over time. Eliminating the changes in the labor distortion does not have an additional significant impact on the pattern of capital accumulation, compared to eliminating the capital distortion. Changes in labor distortions do have a minor impact on the evolution of TFP, though, slowing its growth between 2003-06 and fostering it after 2008. Notice that the average labor distortion is normalized to one, so the impact on TFP is only because of changes in its cross-sectional distribution over time. This is the main mechanism in the literature of misallocation, which we explore in more detail in Meza, Pratap and Urrutia (2016) for this same dataset.

To further illustrate this point, in the last counterfactual we eliminate the sectoral heterogeneity in the changes in distortions, but let the average capital and labor distortions change as in the baseline. That is, in each year, we force distortions in all sectors to grow at the same rate, equal to the observed rate of growth of the average distortion. The results, summarized in Figure 6, show that sectoral heterogeneity in the evolution of distortions play a minor role in affecting capital accumulation. However, it does have an impact in the evolution of TFP, a result that mimics our findings in Meza, Pratap and Urrutia (2016).

5 Credit Conditions and Capital Distortions

Having established that sectoral capital distortions are important to understand the behavior of aggregate investment, we now investigate what lies behind these distortions. In particular, we explore the role of credit conditions in the evolution of these distortions. We present a simple model of a firm's production and investment under financial constraints and show how sector specific financial variables map into the dynamic capital distortions defined in section 2. We also analyze the statistical relation between our panel of dynamic distortions constructed in section 3 and sector specific credit conditions, obtained from the R04C database.

5.1 A Model of Investment with Financial Frictions

The model borrows from the production structure described in section 2. In each period, the representative firm in each sector $i \in \{1, 2, \dots, n\}$ produces output using capital and labor according to the Cobb-Douglas production function (1). Firms maximize the expected present value of profits, defined as sales net of the cost of labor minus investment plus debt accumulation

$$\Pi^i \equiv E_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+\iota} \right)^t \left\{ p_t^i Y_t^i - \theta_t^{L,i} w_t L_t^i - [K_{t+1}^i - (1-\delta) K_t^i] + B_{t+1}^i - (1+r_t^i) B_t^i \right\}$$

where ι is the risk free *lending* rate for firms, that we assume constant while r_t^i denotes the sector-specific interest rate on debt. As before, $\theta_t^{L,i}$ is a labor distortion that we take as a primitive.¹⁰

Notice, however, that there is no longer an explicit dynamic capital distortion. Instead, we assume that firms face the following two financial constraints

$$K_{t+1}^i - (1-\delta) K_t^i \leq B_{t+1}^i - (1+r_t^i) B_t^i \quad (8)$$

$$B_{t+1}^i \leq \phi_t^i. \quad (9)$$

The first constraint forces investment to be financed through debt issuance. The second constraint limits borrowing by a sector specific parameter ϕ_t^i . These financial frictions lead to an investment wedge in the model that mimics the exogenous capital distortion $\theta_t^{K,i}$ in section 2.

5.1.1 Obtaining an Investment Wedge

The sector-specific technologies A_t^i , borrowing tightness ϕ_t^i and interest rate r_{t+1}^i are assumed to be stochastic (notice that r_{t+1}^i is known at date t , since it denotes the interest rate contracted at t and paid at $t+1$). Using $\nu_{1t}^i \left(\frac{1}{1+\iota} \right)^t$ as the multiplier for (8) and $\nu_{2t}^i \left(\frac{1}{1+\iota} \right)^t$ for (9), the Lagrangian for the maximization problem described above can be written as:

$$L_0 = E_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+\iota} \right)^t \left\{ p_t^i Y_t^i - \theta_t^{L,i} w_t L_t^i + (1+\nu_{1t}^i) [B_{t+1}^i - (1+r_t^i) B_t^i - K_{t+1}^i + (1-\delta) K_t^i] + \nu_{2t}^i (\phi_t^i - B_{t+1}^i) \right\}$$

¹⁰It is quite simple to endogenize the labor distortion through a working capital constraint as in Meza, Pratap and Urrutia (2016).

with first order conditions:

$$(1 - \alpha^i) p_t^i \frac{Y_t^i}{L_t^i} = \theta_t^{L,i} w_t \quad (10)$$

$$1 + \nu_{1t}^i = \frac{1}{1 + \iota} E_t \left\{ \alpha p_{t+1}^i \frac{Y_{t+1}}{K_{t+1}} + (1 - \delta) (1 + \nu_{1t+1}^i) \right\} \quad (11)$$

$$1 + \nu_{1t}^i - \nu_{2t}^i = \left(\frac{1 + r_{t+1}^i}{1 + \iota} \right) E_t (1 + \nu_{1t+1}^i) \quad (12)$$

plus the complementary slackness conditions.

The static condition (10) is the same as in the model in section 2. More importantly, the Euler equation with generic investment wedges from that model, reproduced here,

$$\theta_t^{K,i} = \frac{1}{1 + \iota} E_t \left\{ \alpha p_{t+1}^i \frac{Y_{t+1}}{K_{t+1}} + (1 - \delta) \theta_{t+1}^{K,i} \right\}$$

is identical to equation (11) with $\theta_t^{K,i} = 1 + \nu_{1t}^i$. In other words, we can define an endogenous investment wedge in the new model arising from financial frictions.

In this world firms will only borrow to invest in capital provided $r_{t+1} > \iota_t$. To see this, notice that if the constraint (8) does not bind and $\nu_{1t}^i = 0$, then, given the non negativity constraint on multipliers, ν_{2t}^i must also be 0. However, in that case (12) will not hold with equality, i.e.

$$\left(\frac{1 + r_{t+1}^i}{1 + \iota} \right) E_t (1 + \nu_{1t+1}^i) > 1.$$

The complementary slackness conditions imply that B_{t+1}^i must be zero. In other words, the inequality above suggest that the benefits from borrowing to pay out dividends are outweighed by their costs.

5.1.2 Comparative Statics with respect to Credit Conditions

Equation (12) provides a recursive expression for the capital distortion:

$$\theta_t^{K,i} = \nu_{2t}^i + \left(\frac{1 + r_{t+1}^i}{1 + \iota} \right) E_t \theta_{t+1}^{K,i} \quad (13)$$

Solving this equation forward, we obtain that the investment wedge depends on the current *and expected future* values of the interest rate premium paid by each sector (on top of the common base rate ι) and the current and future multipliers of the borrowing limit ν_{2t}^i .

We can use this result to infer how dynamic capital distortions react to credit conditions. Everything else equal, an increase in the sector specific borrowing rate ($r_{t+1}^i \uparrow$) today increases the dynamic capital distortion ($\theta_t^{K,i} \uparrow$). Also, a tightening in the sector specific credit availability ($\phi_t^i \downarrow$) makes the borrowing constraint (9) more likely to bind, also adding to the size of the capital distortion. Next we will test for these theoretical relations in the data.

| Correlations | Credit/ | | |
|---------------------------|--------------|-------------|---------------|
| | Total Credit | Value Added | Interest Rate |
| $\theta_t^{K,i}$ | -0.091 | -0.155 | 0.068 |
| $\overline{\theta^{K,i}}$ | -0.098 | -0.189 | 0.122 |

Table 2: Correlations: Capital Distortions and Credit Conditions

5.2 Testing for Statistical Relations in the Data

We now test for a statistical relationship between our panel of capital distortions constructed in section 3 and sector specific credit conditions (interest rate and credit availability) for the same years. The financial variables are obtained from the R04C credit registry database, which provides information on the universe of loans by commercial banks to firms. We would expect that the interest rate and the capital wedge would be positively related, while an indicator of the availability of credit such as the credit to value added ratio would, by loosening the borrowing constraint, reduce the capital distortion.

5.2.1 Data on Credit Conditions

In Meza, Pratap and Urrutia (2016) we describe how we use the R04C to construct new credit flows and the cost of credit aggregated to the sector level at a yearly frequency. We construct a measure of credit flow by looking at the debt outstanding on all new loans (i.e. loans with dates of disbursement in the month in which the data are collected) in a particular sector. This gives us information on how much credit was disbursed to each sector in each period.¹¹ Finally, we construct measures of the cost of credit by looking at average real interest rates paid by sector, weighted by the size of the loan in the total credit flow in the corresponding period, and deflated by the change in the producer price index for manufacturing.

Figure 7 shows the aggregate credit flow to all sectors as a fraction of value added (we refer to it as credit intensity), while Figure 8 shows the average real interest rate each year. The aggregate credit to value added ratio declined in 2003-05, a period where the average capital distortion was quite high. The increase in credit intensity from 2006-08 also coincided with a reduction in the distortion. The recession of 2009 saw both a fall in credit, and an increase in interest rates. While credit intensity did increase after the recession, it did not recover to the pre-recession levels. Interest rates movements are inversely related to the movements in aggregate credit. The credit boom of 2005-08 was mostly accompanied by falling rates, while the recession saw a spike in the cost of borrowing.

5.2.2 Empirical Evidence

Table 2 shows the simple correlation between the capital distortion and credit conditions. Total credit and credit intensity are negatively related to the investment wedge. This suggests that sectors with greater access to credit are able to align their capital stocks to their optimal values. Higher interest rates are associated with higher values of the distortion. These correlations hold in the panel, as well as between the steady state values of the distortions and the time averaged values of the financial variables.

¹¹In Meza, Pratap and Urrutia (2016) we include only short run credit, since the focus was on working capital. However, because we are now looking at investment, we include loans of all maturities. Results for loans restricted by maturity are available upon request.

| | Dependent Variable $\theta_t^{K,i}$ | | | |
|--------------------|-------------------------------------|----------|---------|--------|
| | (1) | (2) | (3) | (4) |
| Credit/Value Added | -0.722** | -0.030** | | |
| | 0.177 | 0.015 | | |
| Interest Rate | | | 0.184** | 0.011* |
| | | | 0.077 | 0.006 |
| Time Dummies | Yes | Yes | Yes | Yes |
| Sector Effects | No | Yes | No | Yes |

Notes: Standard Errors below estimates. Two stars denote significance at the 5 percent level, and one star denotes 1% significance.

Table 3: Regressions: Capital Distortions and Credit Conditions

Table 3 shows the results of regressing the capital distortion against credit conditions, summarized by the sector specific credit intensities and interest rates. The first two columns show the results for credit intensity, with and without sector specific fixed effects. Sectors with high distortions are those with a lower credit intensity. The last two columns show the results for interest rates. The positive correlation that we observed in the previous table is robust to the inclusion of time dummies and to fixed effects.

Taken together, these statistical relations suggest that credit conditions are important determinants of the dynamic capital distortion. A more detailed model would allow us to quantify the effects of financial constraints on capital accumulation via its effects on the capital distortion. However, our simple exercise shows that they are likely to be important.

6 Conclusions

The availability and cost of bank credit is an important determinant of capital accumulation. We illustrate this in the case for the Mexican manufacturing industry by showing at the disaggregated level that changes in sector specific credit conditions are related to changes in dynamic capital distortions affecting the optimal investment choice. Sectors which experience an increase in the access to credit and/or a decline in the real interest rate reduce their capital distortions, allowing them to get closer to their optimal level of investment. This mechanism turns out to be important for the evolution of aggregate investment in the Mexican manufacturing industry.

A next step in this agenda is to analyze the dynamics of individual firms within each sector, from which we abstract due to the assumption of constant returns to scale. However, as of now such analysis is limited by the availability of firm level data combining real and financial variables in Mexico.

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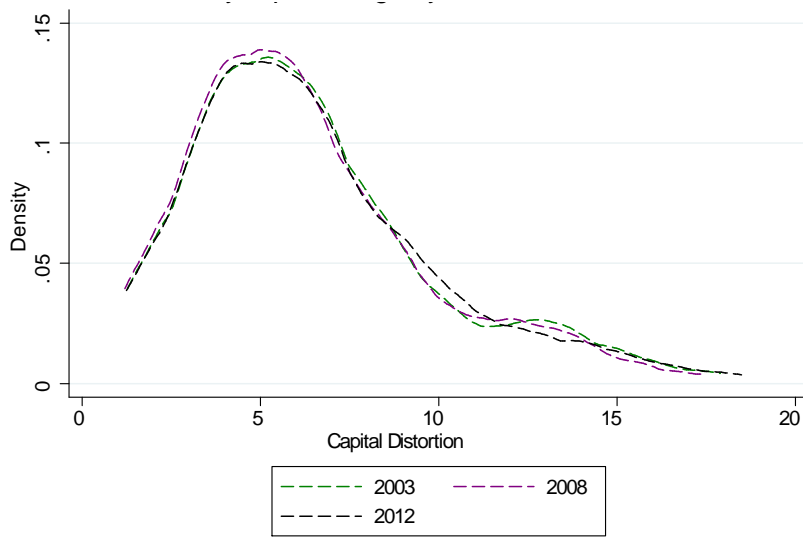


Figure 1: Estimated Kernel Densities for the Capital Distortion

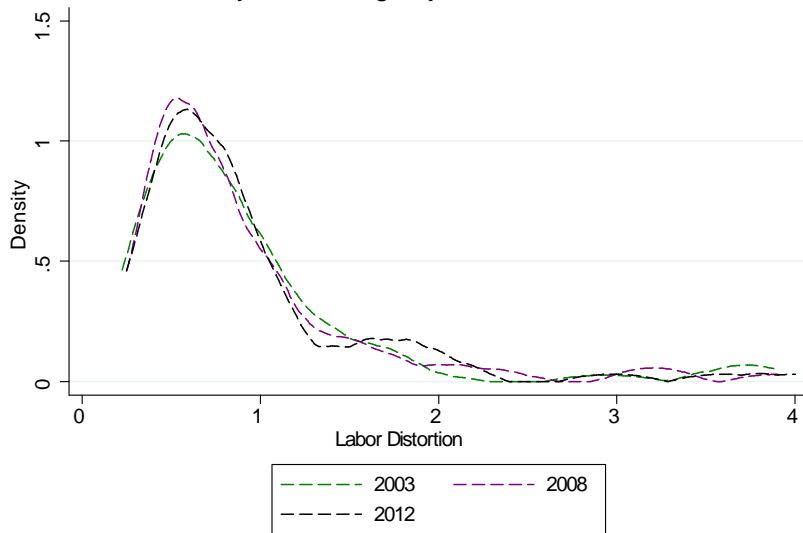


Figure 2: Estimated Kernel Densities for the Labor Distortion

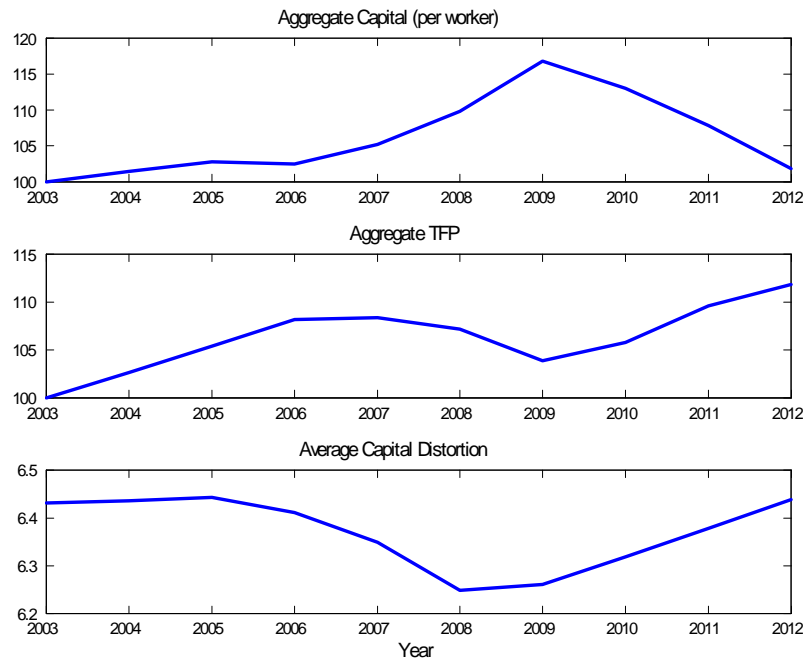


Figure 3: Aggregate Capital, TFP and Average Capital Distortions

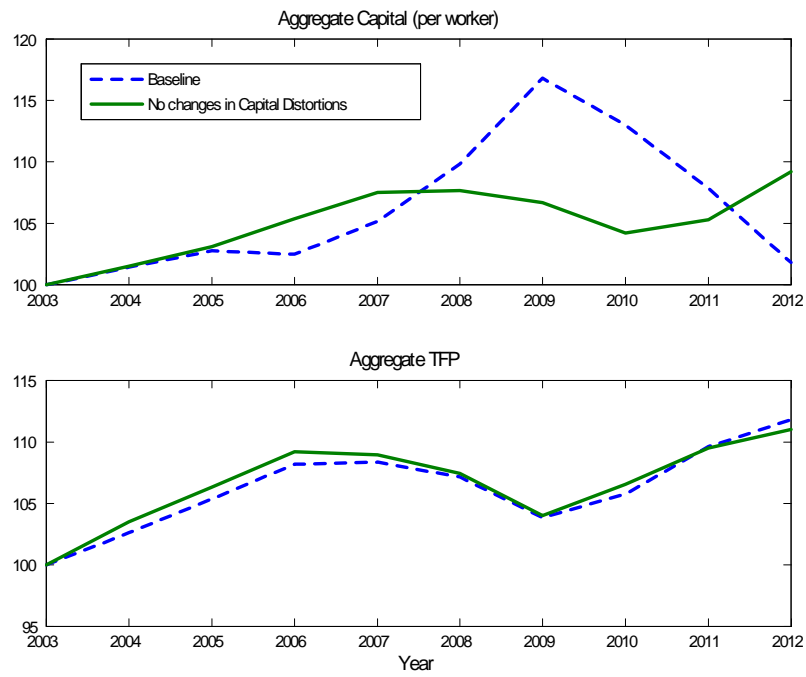


Figure 4: Eliminating Changes in the Capital Distortion

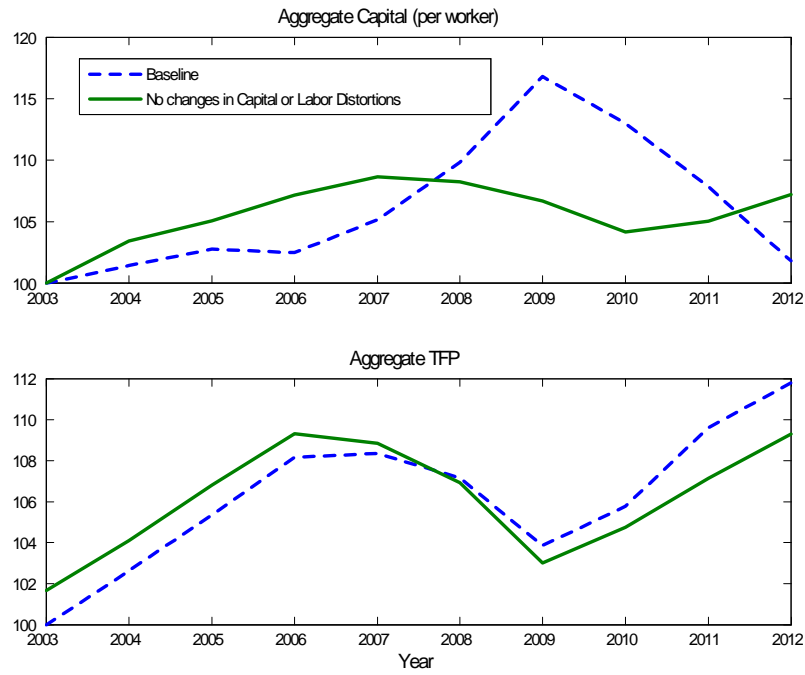


Figure 5: Eliminating Changes in Capital and Labor Distortions

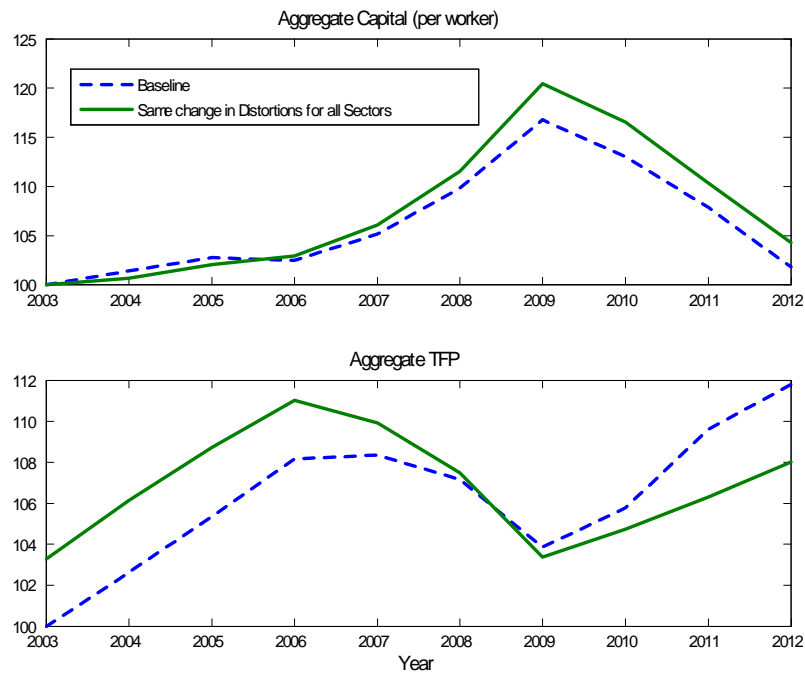


Figure 6: Eliminating Sectoral Heterogeneity in Changes in Distortions

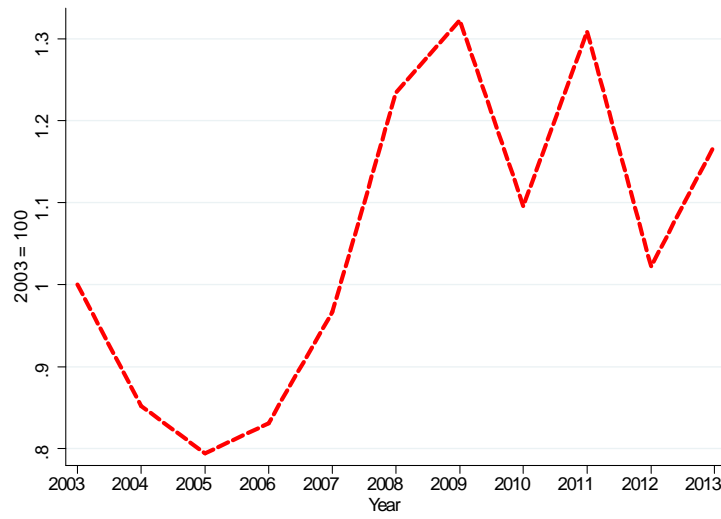


Figure 7: Aggregate Credit to Value Added Ratio, 2003=100

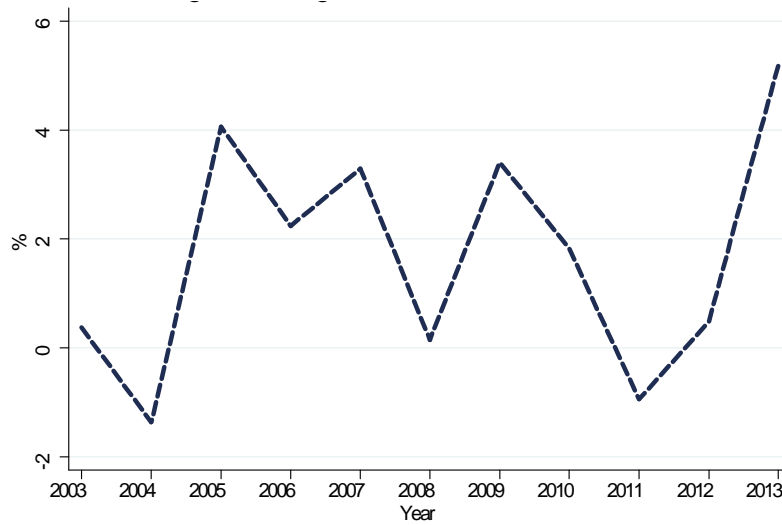


Figure 8: Loan-weighted Average Real Interest Rate, %

A Dynamic Distortions with Intermediate Goods

A.1 The Extended Model

In each period, firms produce sectoral gross output using capital, labor and intermediates according to the Cobb-Douglas production function

$$Y_t^i = A_t^i \left((K_t^i)^{\alpha^i} (L_t^i)^{1-\alpha^i} \right)^{\varepsilon^i} (M_t^i)^{1-\varepsilon^i} \quad i \in \{1, \dots, n\}. \quad (14)$$

The representative firm in each sector maximizes the expected present value of the stream of profits net of investment expenditures

$$\Pi^i \equiv E_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+\iota} \right)^t \left\{ p_t^i Y_t^i - \theta_t^{L,i} w_t L_t^i - \theta_t^{M,i} q_t M_t^i - \theta_t^{K,i} [K_{t+1}^i - (1-\delta) K_t^i] \right\},$$

where $\theta_t^{L,i}$, $\theta_t^{M,i}$ and $\theta_t^{K,i}$ are sector-specific distortions that affect the cost of the labor input, of intermediates, and the cost of investment. The solution of the maximization problem satisfies the first order condition for labor

$$\theta_t^{L,i} w_t L_t^i = (1 - \alpha^i) \varepsilon^i p_t^i Y_t^i$$

intermediates

$$\theta_t^{M,i} q_t M_t^i = (1 - \varepsilon^i) p_t^i Y_t^i$$

and the stochastic Euler equation

$$\theta_t^{K,i} = \frac{1}{1+\iota} E_t \left\{ MRK_{t+1}^i + (1-\delta) \theta_{t+1}^{K,i} \right\},$$

where the marginal revenue of capital in each period is

$$MRK_t^i = \alpha^i \varepsilon^i (p_t^i A_t^i)^{\frac{1}{\varepsilon^i}} \left(\frac{K_t^i}{L_t^i} \right)^{\alpha^i - 1} \left(\frac{M_t^i}{Y_t^i} \right)^{\frac{1-\varepsilon^i}{\varepsilon^i}} = \alpha^i \varepsilon^i (A_t^i)^{\frac{1}{\varepsilon^i}} \left(\frac{K_t^i}{L_t^i} \right)^{\alpha^i - 1} \left(\frac{p_t^i (1 - \varepsilon^i)}{\theta_t^{M,i} q_t} \right)^{\frac{1-\varepsilon^i}{\varepsilon^i}}$$

using the first order condition for intermediates.

The output of each sector is again combined using a Cobb-Douglas aggregator to produce aggregate gross output

$$Y_t^g = \prod_{i=1}^n (Y_t^i)^{\omega^i} = Y_t + \phi M_t. \quad (15)$$

which can be used to satisfy final demand (Y_t) or to create intermediates (M_t) at a constant linear transformation rate ϕ equal to the relative price of intermediates q_t . Summing across all sectors,

$$K_t = \sum_{i=1}^n K_t^i \quad L_t = \sum_{i=1}^n L_t^i \quad M_t = \sum_{i=1}^n M_t^i.$$

With the same normalizations on total labor and the average labor distortions, the sectoral labor equation is now

$$L_t^i = \left(\frac{\omega^i (1 - \alpha^i) \varepsilon^i}{\Phi \theta_t^{L,i}} \right) L_t, \quad (16)$$

with $\Phi = (1 - \alpha) \varepsilon = \varepsilon - \alpha \varepsilon$, $\varepsilon \equiv \sum_{j=1}^n \omega^j \varepsilon^j$, and $\alpha \varepsilon \equiv \sum_{j=1}^n \omega^j \alpha^j \varepsilon^j$. Replacing in the Euler equation, we get

$$\theta_t^{K,i} = \frac{1}{1+\iota} E_t \left\{ \alpha^i \varepsilon^i (p_{t+1}^i A_{t+1}^i)^{\frac{1}{\varepsilon^i}} \left(\frac{\omega^i (1 - \alpha^i) \varepsilon^i}{(1 - \alpha) \varepsilon \theta_{t+1}^{L,i} K_{t+1}^i} \right)^{1-\alpha^i} \left(\frac{1 - \varepsilon^i}{\theta_{t+1}^{M,i} \phi} \right)^{\frac{1-\varepsilon^i}{\varepsilon^i}} + (1 - \delta) \theta_{t+1}^{K,i} \right\}. \quad (17)$$

We assume that the (log of) revenue productivity and the three distortions follow AR(1) stochastic processes with persistences ρ_A , ρ_L , ρ_K and ρ_M . Log-linearizing this equation around the deterministic steady state, we obtain

$$\Psi \widetilde{\theta_t^{K,i}} = \frac{1}{\varepsilon_i} \rho_A \widetilde{p_t^i A_t^i} - E_t (1 - \alpha^i) \widetilde{K_{t+1}^i} - (1 - \alpha^i) \rho_L \widetilde{\theta_t^{L,i}} - \frac{1 - \varepsilon^i}{\varepsilon^i} \rho_M \widetilde{\theta_t^{M,i}} \quad (18)$$

with $\Psi \equiv \frac{(1+\iota)-(1-\delta)\rho_K}{\iota+\delta}$. To solve for the optimal decision rule, we postulate again a linear policy function mapping capital tomorrow to the state variables of the firm:

$$(1 - \alpha^i) \widetilde{K_{t+1}^i} = \gamma \widetilde{K_t^i} + \gamma_A \widetilde{p_t^i A_t^i} + \gamma_K \widetilde{\theta_t^{K,i}} + \gamma_L \widetilde{\theta_t^{L,i}} + \gamma_M \widetilde{\theta_t^{M,i}}. \quad (19)$$

Replacing in (18) and solving as before by the method of indetermined coefficients, we obtain $\gamma = 0$, $\gamma_A = \frac{1}{\varepsilon^i} \rho_A$, $\gamma_K = -\Psi$, $\gamma_L = -(1 - \alpha^i) \rho_L$ and $\gamma_M = -\frac{1 - \varepsilon^i}{\varepsilon^i} \rho_M$. This policy rule allows us to construct sectoral capital sequences for given sequences of revenue productivity and distortions.

A.2 Quantitative Results

Using the U.S. shares and the EIA data on sectoral revenue and inputs (including purchases of intermediate goods), we compute revenue productivity in each sector and year from the production function as

$$p_t^i A_t^i = \frac{p_t^i Y_t^i}{\left((K_t^i)^{\alpha^i} (L_t^i)^{1-\alpha^i} \right)^{\varepsilon^i} (M_t^i)^{1-\varepsilon^i}}$$

and estimate a dynamic panel regression using the Arellano-Bond method. With this information, we compute now the implied capital, labor and intermediates distortions in the model. First, we obtain the static labor wedge from the condition (16), plugging in the observed labor allocation sequences. We compute the intermediates distortions using the first order condition for intermediates:

$$\theta_t^{M,i} q_t M_t^i = (1 - \varepsilon^i) p_t^i Y_t^i$$

and the observed sequences for $q_t M_t^i$ and $p_t^i Y_t^i$. We also compute a panel for the investment wedges from the linearized Euler equation (18), plugging in the observed sectoral revenue productivities, labor distortions, intermediates distortions, and capital sequences, the estimated persistence parameters for productivity and distortions, and using the same iterative procedure described in Section 2.

Table 4 reports the main statistical properties of the capital distortion estimated in the model without intermediate goods (comparable to Table 1 in Section 3 of the main text). The differences are minor. If anything, adding intermediate goods and the corresponding distortion to their use reduces the absolute size of the investment wedge, without changing much its trend over time.

Moreover, as shown in Figure 9, the contribution of the capital distortion to investment and the path of aggregate capital is qualitatively similar to the one obtained in Section 4 without intermediate goods: A reduction in the investment wedge between 2006-08 is associated to an increase in the speed of capital accumulation, while the opposite is observed in 2009-12. Finally, Table 5 (comparable to Table 2 in Section 5 of the main text) confirms that the statistical relation between capital distortions and financial variables is robust to the introduction of intermediate goods. Regression results with fixed effects also confirm this relationship.

| | 2003-05 | 2005-08 | 2008-09 | 2009-12 |
|---|---------|---------|---------|---------|
| Capital Distortion ($\theta_t^{K,i}$) | | | | |
| - Mean | 5.29 | 5.21 | 5.13 | 5.19 |
| - C.V. (std deviation/mean) | 0.73 | 0.68 | 0.65 | 0.64 |
| - Correlation with Employment (L_t^i) | -0.16 | -0.17 | -0.17 | -0.18 |
| - Correlation with Productivity ($p_t^i A_t^i$) | 0.60 | 0.45 | 0.37 | 0.38 |

Table 4: Descriptive Statistics for the Capital Distortions without Intermediate Goods

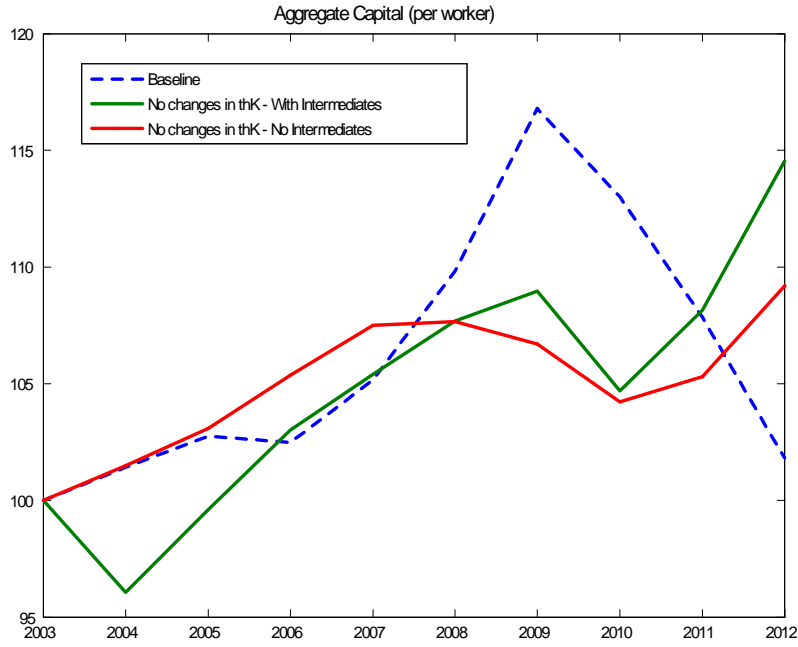


Figure 9: Eliminating Changes in the Capital Distortion with and without Intermediates

| Correlations | Credit/ | | |
|---------------------------|--------------|-------------|---------------|
| | Total Credit | Value Added | Interest Rate |
| $\theta_t^{K,i}$ | -0.126 | -0.065 | 0.030 |
| $\theta^{\overline{K},i}$ | -0.139 | -0.077 | 0.038 |

Table 5: Distortions and Financial Variables