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

This paper documents a transmission channel from credit conditions to capital accumulation via investment wedges at a disaggregated level. We use a simple multi-industry model of production and investment to identify these wedges (i.e., deviations from the optimality condition based on a stochastic Euler equation) from a panel of observations at the 4-digit industry level from Mexican manufacturing. We measure the dynamic distortions in capital accumulation and show that their behavior is important in accounting for changes in the aggregate capital stock over time. We then analyze the sources of these distortions, working with one important candidate: bank credit. Using a simple model of investment with financial frictions, we show that greater availability and cheaper access to credit reduce capital distortions and find empirical support for this mechanism in the data.

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1 Introduction

We analyze the influence of financial factors on firms’ investment decisions and on aggregate capital accumulation via their effect on dynamic capital distortions.\footnote{In a companion piece (Meza, Pratap and Urrutia 2017), we quantify the impact of credit on static input distortions and total factor productivity (TFP). The main message of that paper is that changes in the cost and availability of credit can account for a large extent of the observed changes in aggregate TFP in the Mexican manufacturing industry. Moreover, the variation in credit conditions across industries is key for their impact on the misallocation of resources.} For this, we build a simple multi-industry model of production and investment to measure labor and capital distortions using microdata for the Mexican manufacturing industry. We use the framework to assess the importance of these distortions in accounting for the behavior of capital stock and TFP over time.\footnote{Starting 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 creating distortions in Mexico). Most of this research looks at the level impact of misallocation, not on its effect on time trends. A few exceptions include the work of Chen and Irarrazabal (2015) and Sandleris and Wright (2014) for the cases of Chile and Argentina, respectively.} Furthermore, we estimate how dynamic capital distortions are related to the industry-specific credit intensities and interest rates.

Our analysis is based on a rich industrial structure within Mexican manufacturing and exploits changes observed during a ten year period. We use the merged dataset that we built in Meza, Pratap and Urrutia (2017), linking output, employment and investment with credit flows and interest rates at the 4-digit industry level for the Mexican manufacturing sector (see details in the Appendix). To the best of our knowledge, this is one of the first papers measuring heterogenous dynamic capital distortions and providing an economic content to their evolution over time. The disaggregated dimension is important since, as Buera and Moll (2015) show, the aggregate investment wedge computed from the accounting framework of Chari, Kehoe and McGrattan (2007) can be uninformative about the presence of heterogeneous distortions driven by financial frictions.

The two main results of the paper are as follows: First, changes in dynamic capital distortions are important in accounting for the trajectory of capital accumulation over time. Even though aggregate TFP stagnates between 2006 and 2009, a reduction in the investment wedge is associated with an acceleration of capital accumulation. The reverse is true for 2009-2012; capital accumulation slows down, along with an increase in the capital wedge, despite a rise in aggregate TFP. In our quantitative model, capital distortions are responsible for boosting the annualized rate of growth of capital by 4.1 percentage points in the 2006 - 2009 subperiod, and for depressing this rate by 5.2 percentage points per year between 2009 and 2012. However, unlike static distortions, the effect of dynamic capital distortions on TFP is negligible.

Second, we find a robust link between the evolution of the capital distortion in each industry and industry-specific credit conditions. Industries where the availability of credit falls and/or real interest rates increase experience, on average, an increase in their capital distortions. This result, which we formalize in a simple model of investment with financial frictions, is robust to various empirical specifications and highlights the importance of the banking system in financing investment in Mexican manufacturing. We estimate the contribution of credit conditions to the investment wedge and find that it has a lower bound of about 21 percent for the whole manufacturing sector. Across industries, this lower bound ranges from 4 percent to 85 percent.

A large literature on the effects of financial constraints on firm investment uses both reduced form...
estimates (see Hubbard 1998 for a survey) and structural techniques (Pratap and Rendon 2003, Hennessey and Whited 2007). These papers do not measure 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. (2018) 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 and its implications for TFP.\footnote{In a recent paper, David and Venkateswaran (2018) decompose capital misallocation into various sources and ascribe a large part (more than half) to firm-specific factors which are permanent and/or correlated with firm productivity. For a less developed country like China, they claim that size-dependent policies or certain forms of financial imperfections might be good candidates to generate these types of firm-specific factors.}

The next section sets out an accounting framework within which we measure the impact of dynamic distortions, and section 3 details how they are computed. Section 4 sets out a simple model to evaluate the importance of finance in the evolution of these dynamic distortions. Section 5 concludes.

2 An Investment Model with Industry-Specific Distortions

We set up a simple model of production and investment with multiple \((n)\) industries, 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 and make investment decisions in an uncertain environment. They face industry specific distortions: a static labor wedge and a dynamic investment wedge that we model, for now, as primitives.

2.1 The Investment Problem

Firms produce output using capital and labor according to the Cobb-Douglas production function

\[
Y_i^t = A_i^t \left( K_i^t \right)^{\alpha_i^t} \left( L_i^t \right)^{1-\alpha_i^t} \quad i \in \{1, ..., n\},
\]

where \(A_i^t\) is an industry specific productivity shock. Firms own their capital stock and take prices as given. The representative firm in each industry maximizes the expected present value of the stream of profits net of investment expenditures

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

where \(\theta_t^{L,i}\) and \(\theta_t^{K,i}\) are stochastic industry specific distortions that affect the cost of labor and investment respectively.\footnote{In an online appendix (available upon request) we also include a static distortion to the use of intermediates inputs. Meza, Pratap and Urrutia (2017) show that this margin is quantitatively important for static misallocation and TFP losses, but our results suggest that its dynamic effects on capital accumulation are small.} We assume for now that firms can borrow or lend at the constant, risk free rate \(\iota\).

The solution satisfies the first order condition for labor

\[
\theta_t^{L,i} w_t L_t^i = (1-\alpha_i^t) p_t^i Y_t^i
\]
and the stochastic Euler equation

\[ \theta_t^{K,i} = \frac{1}{1 + \ell} E_t \left\{ \alpha^i p^i_{t+1} A^i_{t+1} \left( K^i_{t+1}/L^i_{t+1} \right)^{1-\alpha^i} \left( \frac{1}{\theta_t^{L,i}} \right) \left( \frac{1}{1 - \delta} \right) \theta_t^{K,i} \right\} + (1 - \delta) \theta_t^{K,i} \].

We assume that the output from all industries is combined to produce aggregate output using a Cobb-Douglas aggregator

\[ Y_t = \prod_{i=1}^{n} (Y_t^i)^{\omega^i}. \]  

(2)

This aggregator implies that the expenditure share in each industry is constant and equal to \( \omega^i \). We can therefore write the static first order condition for labor as

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

normalizing the price of the final good to one. Summing up across industries, we get an expression for aggregate labor,

\[ L_t = \sum_{i=1}^{n} L^i_t = \Phi \frac{Y_t}{w_t}, \]

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

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

(3)

so aggregate labor, the supply of which we take as exogenous, is allocated across industries based on technological parameters and the static labor distortion only.

Two further normalizations simplify our calculations. First, we assume that the aggregate labor input \( L_t = 1 \), so all variables are expressed in per worker terms. We also normalize \( \Phi_t = 1 - \alpha \), with \( \alpha = \sum_{j=1}^{n} \omega^j \alpha^j \). In other words, we assume that the labor distortions cancel out on average. All labor distortions therefore should be interpreted as relative to the (weighted) average aggregate distortion.

### 2.2 Solving the Linearized Euler Equation

Substituting (3) in the Euler equation, results in a stochastic difference equation in the capital distortion \( \theta_t^{K,i} \)

\[ \theta_t^{K,i} = \frac{1}{1 + \ell} E_t \left\{ \alpha^i p^i_{t+1} A^i_{t+1} \left( K^i_{t+1}/L^i_{t+1} \right)^{1-\alpha^i} \left( \frac{1}{\theta_t^{L,i}} \right) \left( \frac{1}{1 - \delta} \right) \theta_t^{K,i} \right\} + (1 - \delta) \theta_t^{K,i} \].

and the long run value of capital in the deterministic steady state

\[ K_t = \left( \frac{\alpha^i p^i A^i}{\theta_t^{K,i}} \right)^{1-\alpha^i} \left( \frac{\omega^i (1 - \alpha^i)}{1 - \delta} \right) \frac{1}{\theta_t^{L,i}}. \]  

(5)

In what follows, we work with the log-linearized version of the Euler equation around this deterministic steady state. Defining deviations from the steady state as \( \bar{x}_t = \log (x_t) - \log (\bar{x}) \) and using the steady state capital condition (5), we can approximate the Euler equation in log-deviations by:

\[ \bar{\theta}_t^{K,i} = \frac{1}{1 + \ell} \left\{ (\ell + \delta) E_t \left[ p^i_{t+1} A^i_{t+1} - (1 - \alpha^i) \left( \bar{K}^i_{t+1} + \bar{\theta}_t^{L,i} \right) \right] + (1 - \delta) E_t \bar{\theta}_t^{K,i} \right\}. \]
We further assume that (the log of) revenue productivity $p_i^t A^i_t$, and the two distortions $\theta_{K,i}^t$ and $\theta_{L,i}^t$ follow first order autoregressive processes with persistence parameters $\rho_I^j$ and i.i.d white noise $\varepsilon_{it}^J$ for $J = A, K, L$.

$$
\log (p_{i+1}^t A_{i+1}^i) = \log (p_i^t A^i_t) + \rho_A^i \log (p_i^t A^i_t) + \varepsilon_{it}^A
$$

$$
\log \theta_{K,i}^t = \log \theta_{K,i}^{t-1} + \rho_K^i \log \theta_{K,i}^{t-1} + \varepsilon_{it}^K
$$

$$
\log \theta_{L,i}^t = \log \theta_{L,i}^{t-1} + \rho_L^i \log \theta_{L,i}^{t-1} + \varepsilon_{it}^L
$$

We can therefore write the linearized Euler equation as

$$
\Psi_t^i \theta_{K,i}^{t-1} = \rho_A^i p_i^t A_i^t - E_t (1 - \alpha^i) K_{i+1}^t - (1 - \alpha^i) \rho_L^i \theta_{L,i}^{t-1}
$$

(6)

with $\Psi^i = \frac{(1+\varepsilon)(1-\delta)\rho_K}{\bar{e}+\delta}$.

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

$$
(1 - \alpha^i) K_{i+1}^t = \gamma^i K_{i+1}^t + \gamma_A^i p_i^t A_i^t + \gamma_K^i \theta_{K,i}^{t-1} + \gamma_L^i \theta_{L,i}^{t-1}.
$$

(7)

Replacing in (6) and solving, we obtain

$$
\gamma^i K_{i+1}^t + (\gamma_A^i - \rho_A^i) p_i^t A_i^t + (\gamma_K^i + \Psi^i) \theta_{K,i}^{t-1} + [\gamma_L^i + (1 - \alpha^i) \rho_L^i] \theta_{L,i}^{t-1} = 0
$$

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

### 2.3 Aggregating Capital, Output and TFP

The policy function (7) allows us to construct a sequence of the capital stock for given sequences of revenue productivity and distortions for each industry. We can get the aggregate capital stock by adding up capital stock across industries. Using the production function (1) for each industry and the static labor allocation (3), we also obtain a measure of aggregate output as a function of capital allocation (which depends on all distortions), revenue productivities, the labor distortions and the technology parameters.

$$
Y_t = \sum_{i=1}^n p_i^t A_i^t (K_i^t)^{\alpha^i} \left( \frac{\omega^i (1 - \alpha^i)}{(1 - \alpha) \theta_{L,i}^{t-1}} \right)^{1-\alpha^i}
$$

Recall that since we have normalized aggregate labor to 1, aggregate capital and output are expressed in per worker terms. Finally, we define aggregate measured TFP as the ratio $Y_t / K_t^\alpha$.

### 3 Measuring Distortions

Using the framework from the previous section we recover the distortions from the observed revenue productivities, labor and capital stock. We use annual data from the Mexican industrial manufacturing survey (EIA) from 2003 to 2013, aggregated to the 4-digit NAICS classification. Once we exclude industries with missing information and one clear outlier (Oil products and derivatives), we have 82 industries within manufacturing ($n = 82$). For each industry, we construct value added as the difference between gross output and
intermediate goods. Capital stock is constructed using the perpetual inventory method. The labor input is measured as the number of people hired directly and indirectly by all firms.

Following Hsieh and Klenow (2009), we use the capital share from the corresponding industries in the U.S. for 2003, as a benchmark undistorted economy. We then compute revenue productivity in each industry and year from the production function as

\[ p_i^t A_i^t = \frac{p_i^t Y_i^t}{(K_i^t)^{\alpha_i} (L_i^t)^{1-\alpha_i}}. \]

With this information we estimate long run values and persistence parameters of the productivity process via a dynamic panel estimator using the Arellano-Bond method. For the purposes of estimation, \( \rho_A^i \) is estimated separately for each two digit industry (NAICSS 31, 32 and 33) and the steady state values for each 4 digit industry are recovered as the fixed effects of these regressions.

### 3.1 Recovering Capital and Labor Distortions

We can also retrieve the model implied capital and labor distortions from the data. We obtain the labor distortion \( \theta_{iL}^t \) from equation (3), using the panel of labor (normalized by the aggregate). We also compute a panel for the investment wedges from the linearized Euler equation (6), substituting the panel of revenue productivities, labor distortions and capital stock. Notice that because of its dynamic nature we lose one observation, so the resulting panel of distortions only covers the period 2003-12.

To compute \( \theta_{iK}^t \) we need a value for the persistence of the distortions, \( \rho_K^i \) and \( \rho_L^i \). \( \rho_K^i \) is estimated from the labor distortions series, using the Arellano-Bond dynamic panel estimator. As in the estimation of revenue productivity, we estimate the persistence parameter for three separate 2 digit industries and the steady state values as the fixed effect.

For the parameters of the investment wedge, we follow an iterative procedure: Given our estimates of \( \rho_L^i \) and \( \rho_A^i \), we start with an initial guess for \( \rho_K^i \), the implied \( \theta_{iK}^t \) and \( \bar{K}_i^t \) which we use to compute the investment wedges with the linearized Euler equation (6) for each industry and year. We use this panel of investment wedges to update the estimates of \( \rho_K^i \) and \( \bar{K}_i^t \) using the Arellano-Bond estimator. These updated values are plugged into equation (6) again, to give us a new series on the capital distortion. We repeat this process till the estimates converge. As with the estimations of the other two processes, we estimate the persistence parameter at the two digit level, and the steady state values as the fixed effects of these estimations.

The distribution of the capital and labor distortions across the 82 industries is shown in the two panels of Figure 1. That there are almost no industries with undistorted investment \( \theta_{iK}^t = 1 \) and in fact, many industries are experience substantial distortions. The labor distortion in contrast, is relatively smaller and less dispersed.

---

5 We use a steady-state assumption to calculate the initial capital stock in each industry, and then update it using investment flows and the average depreciation rate (\( \delta \approx 0.08 \)). We define investment as the sum of all purchases of investment goods, including structures and equipment. Value added is deflated by the manufacturing PPI and investment by an investment goods deflator to obtain real values.

6 The shares \( \omega_i \) are computed from the EIA dataset as the value added generated by industry \( i \) relative to the total value added in manufacturing.
3.2 Dynamic Distortions, TFP and Capital Accumulation

Using the estimated panels of distortions we can back out the allocations in the baseline economy. Starting from the observed initial capital stock in each industry, 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 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.

Figure 2 plots the capital distortions, averaged across all industries, over time and compares it to the aggregate capital stock (per worker) and TFP in the baseline economy. As expected, 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 following years TFP recovers but capital accumulation does not.

Starting from this benchmark, we perform a set of counterfactual experiments. The first counterfactual keeps the capital distortion constant at its long run value for each industry 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 the first panel of Figure 3 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.

Comparing the first counterfactual with the baseline, we find in our model that capital distortions are responsible for boosting the rate of growth of capital by 4.1 percentage points per year between 2006 and 2009 (i.e., the annualized rate of growth of capital per worker for the period was 4.5%, and it would have been 0.4% without changes in capital distortions). In contrast, capital distortions depressed the rate of capital accumulation by 5.2 percentage points per year between 2009 and 2012. This confirms the quantitative importance of dynamic capital distortions in shaping the incentives to invest. Notice, however, that their impact on TFP changes over time is negligible.

In the second counterfactual we eliminate the industrial 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 industries to grow at the same rate, equal to the observed rate of growth of the average distortion. The results, summarized in the second panel of Figure 3, show that industrial heterogeneity in the evolution of distortions plays a minor role in investment and capital accumulation. However, it does have an impact in the evolution of TFP, a result that mimics our findings in Meza, Pratap and Urrutia (2017).

4 Credit Conditions and Capital Distortions

We now present a simple model of a firm’s production and investment under financial constraints and show how industry specific financial variables map into the dynamic capital distortions defined in section 2.

The model uses the production structure described in section 2 and adds a financial decision for the firm. In each period, the representative firm in each industry $i \in \{1, 2, .., n\}$ produces output using capital and labor according to the Cobb-Douglas production function (1). Firms maximize the expected present
Figure 1: Estimated Kernel Densities for Distortions (across industries)

Figure 2: Aggregate Capital, TFP and Distortions

Figure 3: Counterfactual Experiments
value of dividends, defined as sales net of the cost of labor minus investment plus debt accumulation

\[ \Pi^i = E_0 \sum_{t=0}^{\infty} \left( \frac{1}{1 + \iota} \right)^t \left\{ p^i Y^i_t - \theta^L i w^i_t L^i_t - [K^i_{t+1} - (1 - \delta) K^i_t] + B^i_{t+1} - (1 + r^i_t)B^i_t \right\} \]

where \( \iota \) is the risk free lending rate for firms, that we assume constant. \( r^i_t \) denotes the industry-specific interest rate on debt. As before, we take the labor distortion \( \theta^L i \) as a primitive.\(^7\)

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

\[ K^i_{t+1} - (1 - \delta) K^i_t \leq B^i_{t+1} - (1 + r^i_t)B^i_t \]  
\[ B^i_{t+1} \leq \phi^i_t. \]

The first constraint implies that investment is financed through debt, i.e firms cannot accumulate their dividends. The second constraint limits borrowing by a industry specific parameter \( \phi^i_t \).\(^8\) These financial frictions lead to an investment wedge in the model that mimics the exogenous capital distortion \( \theta^K i \) in section 2.

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

\[ L_0 = E_0 \sum_{t=0}^{\infty} \left( \frac{1}{1 + \iota} \right)^t \left\{ p^i Y^i_t - \theta^L i w^i_t L^i_t + (1 + \nu^i_{1t}) \left[ B^i_{t+1} - (1 + r^i_t)B^i_t - K^i_{t+1} + (1 - \delta) K^i_t \right] + \nu^i_{2t} (\phi^i_t - B^i_t) \right\} \]

with first order conditions:

\[ (1 - \alpha^i) p^i_t Y^i_t L^i_t = \theta^L i w^i_t \]  
\[ 1 + \nu^i_{1t} = \frac{1}{1 + \iota} E_t \left\{ \alpha p^i_{t+1} Y^i_{t+1} + (1 - \delta) (1 + \nu^i_{1t+1}) \right\} \]
\[ 1 + \nu^i_{1t} - \nu^i_{2t} = \left( \frac{1 + r^i_{t+1}}{1 + \iota} \right) E_t (1 + \nu^i_{1t+1}) \]

plus the complementary slackness conditions.

The static condition (10) is the same as in the model in section 2. Defining \( 1 + \nu^i_{1t} = \theta^K i \) we can rewrite the Euler equation as

\[ \theta^K i \left( \frac{1}{1 + \iota} \right)^t E_t \left\{ \alpha p^i_{t+1} Y^i_{t+1} + (1 - \delta) \theta^K i_{t+1} \right\} \]

which is identical to the Euler equation with generic investment wedges in Section 2. In other words, we can define an endogenous investment wedge in the new model arising from financial frictions.

\(^7\)It is quite simple to endogenize the labor distortion through a working capital constraint as in Meza, Pratap and Urrutia (2017).

\(^8\)There is a large literature that uses collateral based borrowing constraints as in Kiyotaki and Moore (1997) or that embed optimal borrowing contracts into models of firm dynamics (see for example Albuquerque and Hopenhayn (2004)). We use a simpler specification since our main concern is to motivate sources of dynamic misallocation.
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 \( \nu^i_{1t} = 0 \), then, given the non negativity constraint on multipliers, \( \nu^i_{2t} \) must also be 0. However, in that case (12) will not hold with equality, i.e.

\[
\left( \frac{1 + r^i_{t+1}}{1 + \iota_t} \right) E_t \left( 1 + \nu^i_{1t+1} \right) > 1.
\]

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

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

\[
\theta^K_{t} = \nu^i_{2t} + \left( \frac{1 + r^i_{t+1}}{1 + \iota_t} \right) E_t \theta^K_{t+1}.
\]

Solving forward, we can see that the investment wedge depends on the current and expected future values of the interest rate premium paid by each industry (on top of the common base rate \( \iota \)) and the current and future multipliers of the borrowing limit \( \nu^i_{2t} \).

We can use this result to infer how dynamic capital distortions react to credit conditions. Everything else equal, an increase in the industry specific borrowing rate (\( r^i_{t+1} \)) today increases the dynamic capital distortion (\( \theta^K_{t} \)). Also, a tightening in the industry specific credit availability (\( \phi^i_t \)) makes the borrowing constraint (9) more likely to bind, also adding to the size of the capital distortion.

Furthermore, if we assume that \( \nu^i_{2t} = 0 \) i.e. the borrowing constraint does not bind, we can construct a lower bound for the capital distortion. Taking logs on both sides of (13) and assuming that \( \theta^K_{t} \) follows an AR(1) process with persistence parameter \( \rho_k \), we can rewrite this equation as

\[
\log \theta^K_{t} \simeq \frac{(r^i_{t+1} - \iota)}{1 - \rho_k}
\]

In other words, in the absence of binding constraints, the dynamic distortion will depend only on the spread between the industry specific interest rate and the risk-free rate.

### 4.1 Empirical Evidence

We now test the empirical predictions of our model. Equation (13) implies that the dynamic wedge in each industry will be positively related to interest rates and inversely to credit availability. Using the financial variables from the R04C credit registry database, which provides information on the universe of loans by commercial banks to firms, we construct a measure of total credit and interest rates to test these propositions.\(^9\)

The top panel of Table 1 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 industries with greater access to credit are able to align their capital stocks closer 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.

The bottom panel of Table 1 shows the results of panel regressions of the capital distortion against credit conditions, summarized by the industry specific credit intensities and interest rates. The first two

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\(^9\)The definition and construction of variables is described in greater detail in Appendix A.
### Table 1: Capital Distortions and Credit Conditions

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Max</th>
<th>Min</th>
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<td>0.19</td>
<td>0.84</td>
<td>0.04</td>
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<td>$\theta^{K,t}_{\text{DATA}}$</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$\theta^{K,t}_{(\text{MODEL})}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\theta^{K,t}_{(\text{DATA})}$</td>
<td>0.21</td>
<td>0.18</td>
<td>0.87</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Notes: Standard errors below coefficients. An asterisk denotes significance at the 5 percent level.

### Table 2: Model and Data Distortions: The Role of Interest Rates

Columns show the results for credit intensity, with and without industry 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 results support the predictions of our model, suggesting that credit conditions are important determinants of the dynamic capital distortion.

Finally, we construct the lower bound on the industry specific distortion using equation (14). This is the distortion predicted by the model when borrowing constraints do not bind and is constructed using the information on interest rates and a risk free rate of 2.5 percent. We follow an iterative procedure similar to the one described in Section 3. Starting with an arbitrary value of $\rho^i_k$, we construct a panel for $\log \theta^{K,t}_{i}$. Using the Arellano-Bond estimator, we estimate an autoregressive process and update the guess for $\rho^i_k$ till it converges. As in Section 3 we estimate the persistence parameter for each 2 digit industry and the steady state values for all 82 industries.

Comparing this distortion to the estimate of the dynamic distortion from the data in Section 3 gives us a lower bound for the contribution of credit conditions. Table 2 shows that the magnitude of the distortion attributable to interest rate spreads accounts for 21 percent of the total dynamic distortion for the whole manufacturing sector, both in and out of steady state. The importance of these spreads varies across industries from 4 percent for NAICS 3122 “Tobacco manufacturing” to 85 percent for NAICS 3231 “Printing and printing support activities”.

<table>
<thead>
<tr>
<th></th>
<th>Credit/Value Added</th>
<th>Interest Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit/Value Added</td>
<td>-0.738*</td>
<td>0.159</td>
</tr>
<tr>
<td>Interest Rate</td>
<td>-0.712*</td>
<td>0.158</td>
</tr>
<tr>
<td>Time Dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>2-Digit Industry Effects</td>
<td>No</td>
<td>Yes</td>
</tr>
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</table>
5 Conclusions

We explore the role of dynamic distortions in explaining capital accumulation and TFP growth. We find that they exert a significant influence on the former, but play a relatively minor role in the movements in the latter. Even though aggregate TFP stagnates between 2006 and 2009, capital accumulation accelerates in this period, as a result of a reduction in the investment wedge. The reverse is true for 2009-2012, i.e., capital accumulation slows down, despite a rise in aggregate TFP, consistent with the observed increase in the average capital distortion. We also find a robust empirical link between the observed changes in the capital distortion for each industry and the industry-specific, credit conditions. Sectors for which credit availability decreases and/or real interest rates increase experience, on average, an increase in their capital distortions. In the context of a simple model of financial frictions, we are also able to construct a lower bound for the effect of financial frictions on the dynamic distortions. We find that interest rate spreads can explain on average about 21 percent of the capital distortions, but the effect varies from 4 percent to 85 percent. These findings highlight the importance of the banking system in financing investment in Mexican manufacturing.

References


A Data Appendix

We have two main data sources: The first is the annual industrial survey (EIA for its acronym in Spanish) collected by the Mexican statistical agency INEGI. The second source is the R04C credit registry maintained by the banking regulatory authority, the Comision Nacional Bancaria y de Valores. Confidentiality restrictions prohibit us from analyzing the data at the firm or loan level. Consequently, we work at the lowest level of aggregation currently feasible, the 4-digit industry level, following the 2007 North American Industrial Classification System (NAICS). The EIA dataset is a representative sample of nearly 7000 manufacturing establishments with information on all 86 4-digit industries. Four industries had missing information for some years, so we dropped them from the sample. The R04C dataset includes information on the universe of loans by commercial banks to firms.

Variables from INEGI’s Encuesta Industrial Anual (EIA) The following variables, except for the capital stock that we construct, are available yearly and aggregated across all firms within each industry: Gross Output is defined as the value of all production. This was cross-checked against an alternative value of gross output, namely the value of sales of the establishment plus change in inventories of finished goods; Intermediate Goods are defined as the sum of expenditures on raw materials, packaging, fuels and energy; Value Added is computed as gross output less intermediate goods; Wage Bill includes all salaries and compensation to workers; Labor is the sum of all male and female personnel employed directly and indirectly by the establishment. The latter includes labor provided by independent contractors; Investment includes all purchases of investment goods, including structures and equipment. Real investment is obtained deflating nominal investment by the manufacturing PPI index; Depreciation refers to all depreciation allowances. The depreciation rate is obtained dividing depreciation by the total value of assets, also obtained from the EIA dataset; Capital Stock is constructed using the perpetual inventory method. We use initial real investment and a steady-state assumption to calculate the initial capital stock. We then update the real capital stock using investment flows and the industry specific depreciation rate. The nominal capital stock is obtained multiplying the real capital stock by the manufacturing PPI index.

Variables from CNBV’s Credit Registry (R04) The R04C variables are gathered at a monthly frequency. To make them compatible with the EIA variables, we aggregate financial data to the annual level. Credit flow is constructed as the debt outstanding on all new loans (i.e. loans with dates of disbursement in the month in which the data is collected) to all firms in a particular industry. We consider new loans of all maturities. We sum the resulting flows for all months in a year to aggregate them at an annual frequency; and Interest rate refers to the average real interest rates reported for all new loans to a particular industry. The average is weighted by the size of the loan in the total credit flow to this industry in the corresponding period. After aggregating it to an annual frequency, we construct the real interest rate by subtracting a measure of inflation based on the producer price index for manufacturing from the nominal rate.

Matching EIA and R04C Industry Classifications In the R04C dataset, the industry of economic activity (industry) at the loan level from December 2001 to June 2009 is classified according to an internal CNBV classification. The data for the period July 2009 to July 2012, like that of the EIA, is classified according to the more standard NAICS 2007. To map the earlier R04 data into the NAICS 2007 classification we need a crosswalk that tells us how to reclassify each category. The credit data we have was provided by the CNBV. We did not receive the disaggregated data which contains each particular credit issued during the December 2001-July 2012 period but were given the
disaggregated (and anonymized) data for the period January 2009-December 2009. This data is especially useful for our purpose since it contains individual credit data for 6 months before and after the classification system changed. We used this data to build the crosswalk using a revealed reclassification method in which we make the mapping among both classifications by observing where each credit was originally classified and were it was reclassified once the classification system changed between June and July 2009. Further details of this method can be found in Meza, Pratap and Urrutia (2017).