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Credit and investment distortions: Evidence from Mexican manufacturing[☆]

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ABSTRACT

We document a transmission channel from credit conditions to capital accumulation via investment wedges. Using a simple multi-industry model of production and investment, we measure these wedges at the 4-digit industry level from Mexican manufacturing and show that they account for most of the changes in aggregate capital over time. We also find a robust relation between the wedges and financial variables: credit and interest rates, also measured at the industry level.

1. Introduction

We analyze the influence of financial factors on firms' investment decisions and aggregate capital accumulation via their effect on dynamic capital distortions. We build a multi-industry model to measure labor and investment wedges using data for the Mexican manufacturing sector (for 2003–12) and assess their importance in accounting for aggregate capital and TFP over time. We also estimate how investment wedges are related to industry-specific credit intensities and interest rates. Our analysis is based on the merged dataset in Meza et al. (2019), linking output, employment and investment with credit flows and interest rates at the 4-digit industry level.[1]

The two main results are: (i) Changes in dynamic capital distortions are important in accounting for the path of capital over time. Although 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. (ii) Industry specific investment wedges and credit conditions are correlated. Industries where the availability of credit falls and/or real interest rates increase experience an increase in their capital distortions. This result is robust to alternative specifications and highlights the importance of the banking system in financing investment in Mexican manufacturing.[2]

To our knowledge, this is one of the first papers measuring heterogeneous investment wedges and providing economic content to their evolution over time. Starting with Hsieh and Klenow (2009) a growing body of research measures *static* heterogeneous distortions on input use across establishments, firms, or industries. Most of this literature analyzes the *level* impact of misallocation, not on its effect on trends.[3] Some recent papers have estimated *dynamic* capital wedges using firm-level panel datasets for the US and China (see Song and Wu, 2015; David and Venkateswaran, 2019), identifying capital misallocation from other distortions arising from capital adjustment costs, market power or information frictions. However, they do not use their framework to account for changes in aggregate capital over time nor do they go further in explaining the remaining idiosyncratic components of investment wedges.

2. A model with industry-specific distortions

There are n industries, each characterized by a representative firm in a perfectly competitive market facing two exogenous industry-specific distortions: a static labor wedge and a dynamic

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1 Meza et al. (2019) quantifies the impact of credit on *static* input distortions and total factor productivity (TFP). See the online appendix (Link) for details of the merged panel dataset.

2 We explore alternative specifications in the online appendix (Link).

3 A few exceptions are Sandleris and Wright (2014) and Chen and Irarrazabal (2015). More related to our work, Gopinath et al. (2017) link the evolution of static capital wedges over time to changes in credit conditions for Southern European countries in a model with financial frictions.

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investment wedge. Firms produce according to

$$Y_t^i = A_t^i \left(K_t^i\right)^{\alpha^i} \left(L_t^i\right)^{1-\alpha^i} \qquad i \in \{1, \ldots, n\}. \tag{1}$$

A_t^i is an industry-specific productivity shock. Firms own their capital stock and maximize the expected present value of profits net of investment expenditures

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

$\theta_t^{L,i}$ and $\theta_t^{K,i}$ are stochastic industry-specific distortions that affect the cost of labor and investment.[4] Firms discount the future at the constant risk-free rate ι. The output from all industries is combined to produce aggregate output

$$Y_t = \prod_{i=1}^{n} \left(Y_t^i\right)^{\omega^i}, \tag{2}$$

implying a constant expenditure share ω^i in each industry.

2.1. Static labor allocation

The first-order condition for labor is

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

normalizing the price of the final good to one. It follows that

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

where $L_t = \sum_{i=1}^n L_t^i$ and the aggregate labor share is $\Phi_t \equiv \sum_{j=1}^n \frac{\omega^j\left(1-\alpha^j\right)}{\theta_t^{L,j}}$. The exogenous supply of labor is allocated across industries based on technological parameters and the labor distortion. Two further normalizations simplify calculations: $L_t = 1$, and $\Phi_t = \Phi = 1 - \Sigma_{j=1}^n \omega^j \alpha^j$ is constant. This implies that all variables are expressed in per worker terms and industry specific labor distortions are relative to the (weighted) average distortion.

2.2. The dynamic Euler equation

Investment in industry i is characterized by the Euler equation

$$\theta_t^{K,i} = \frac{1}{1+\iota} E_t \left\{ \underbrace{\alpha^i p_{t+1}^i A_{t+1}^i \left(K_{t+1}^i / L_{t+1}^i\right)^{\alpha^i - 1}}_{MRK_{t+1}^i} + (1-\delta)\, \theta_{t+1}^{K,i} \right\}$$

Substituting (3) and log-linearizing around the steady state,

$$\widetilde{\theta_t^{K,i}} = \frac{1}{1+\iota} \Big\{ (\iota+\delta)\, E_t \left[\widetilde{p_{t+1}^i A_{t+1}^i} - \left(1-\alpha^i\right)\left(\widetilde{K_{t+1}^i} + \widetilde{\theta_{t+1}^{L,i}}\right)\right] + (1-\delta)\, E_t \widetilde{\theta_{t+1}^{K,i}} \Big\},$$

where $\widetilde{x_t^i} \equiv \log\left(x_t^i\right) - \log\left(\overline{x}^i\right)$. Assuming that (the log of) $p_t^i A_t^i$, $\theta_t^{K,i}$ and $\theta_t^{L,i}$ follow first-order autoregressive processes with persistence parameters ρ_J^i and i.i.d white noise ε_{it}^J, for $J = A, K, L$, the Euler equation is

$$\Psi^i \widetilde{\theta_t^{K,i}} = \rho_A^i \widetilde{p_t^i A_t^i} - E_t \left(1-\alpha^i\right) \widetilde{K_{t+1}^i} - \left(1-\alpha^i\right) \rho_L^i \widetilde{\theta_t^{L,i}} \tag{4}$$

with $\Psi^i \equiv \frac{(1+\iota)-(1-\delta)\rho_K^i}{\iota+\delta}$. We postulate a policy function with undetermined coefficients:

$$\left(1-\alpha^i\right) \widetilde{K_{t+1}^i} = \gamma^i \widetilde{K_t^i} + \gamma_A^i \widetilde{p_t^i A_t^i} + \gamma_K^i \widetilde{\theta_t^{K,i}} + \gamma_L^i \widetilde{\theta_t^{L,i}}, \tag{5}$$

which, substituted in Eq. (4), yields

$$\gamma^i \widetilde{K_t^i} + \left(\gamma_A^i - \rho_A^i\right) \widetilde{p_t^i A_t^i} + \left(\gamma_K^i + \Psi^i\right) \widetilde{\theta_t^{K,i}} + \left[\gamma_L^i + \left(1-\alpha^i\right)\rho_L^i\right] \widetilde{\theta_t^{L,i}} = 0$$

with $\gamma^i = 0$, $\gamma_A^i = \rho_A^i$, $\gamma_K^i = -\Psi^i$ and $\gamma_L^i = -\left(1-\alpha^i\right)\rho_L^i$. The policy function (5) allows us to construct a sequence of capital stock for given sequences of revenue productivity and distortions.

2.3. Aggregation

We obtain the total capital stock by aggregating capital across industries. Using the production function (1) and the static labor allocation (3), we obtain aggregate output per worker as a function of capital allocation, revenue productivities, labor distortions and technology parameters

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

Finally, aggregate measured TFP is Y_t / K_t^{α}.

3. Measuring labor and investment wedges

We recover the distortions from the observed revenue productivities, labor, and capital stocks, using annual data from the Mexican industrial manufacturing survey (EIA) from 2003 to 2013, aggregated to the 4-digit NAICS classification. Excluding industries with missing information and one outlier (oil products and derivatives), we have 82 manufacturing industries.[5]

Following Hsieh and Klenow (2009), we use US data for α^i. We compute revenue productivity

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

and estimate persistence parameters ρ_A^i separately for each 2-digit industry using the Arellano–Bond estimator. The steady state values are recovered as the fixed effect for each 4-digit industry. The labor wedge $\theta_t^{L,i}$ is computed from Eq. (3) and its persistence ρ_L^i and steady state values are estimated similarly. The value added shares ω^i are computed from the EIA.

For the investment wedge, we follow an iterative procedure. Given estimates of ρ_L^i and ρ_A^i, we start with an initial guess for ρ_K^i, the implied steady state values $\overline{\theta^{K,i}}$ and $\overline{K^i}$ and compute the investment wedges with the linearized Euler equation (4). We use these to update the estimates of ρ_K^i and $\overline{\theta^{K,i}}$ using the Arellano–Bond estimator and repeat until parameters converge.

The distributions of the investment wedges are shown in Fig. 1. There are almost no undistorted industries $\left(\theta_t^{K,i} = 1\right)$ and many industries experience substantial distortions. The labor wedges are relatively smaller and less dispersed.[6]

4. Dynamic distortions, TFP and capital accumulation

Using the wedges we compute allocations in the baseline economy. Starting from observed initial capital stocks, we iterate on the policy rule (5) to construct sequences of capital for 2003–12. Using (3), we obtain a panel for labor, so output can be

[4] In the online appendix B (Link), we include a static distortion on intermediates inputs. Meza et al. (2019) show that this margin is quantitatively important for static misallocation and TFP losses. Our results suggest that its dynamic effects on capital accumulation are small.

[5] See online appendix A (Link) for a data description.

[6] Summary statistics for the distribution of the two wedges can be found in the online appendix (Link).

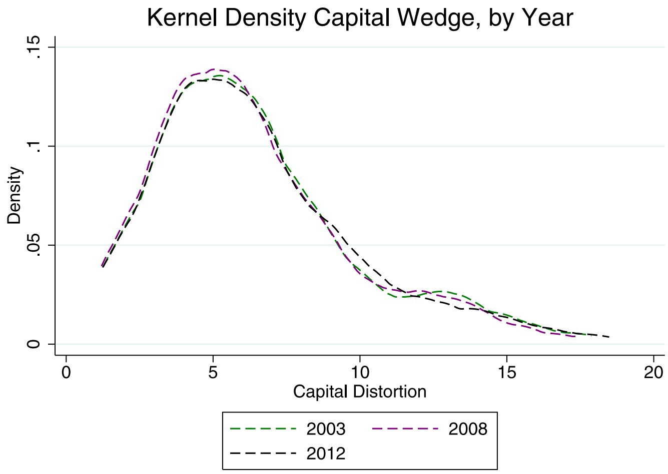

Fig. 1. Estimated Kernel densities for investment wedges.

computed from the technology (1). We aggregate output and capital to compute aggregate TFP. By construction, these allocations match the data exactly.

The solid line in Fig. 2 plots the average dynamic capital distortions over time and compares it to aggregate capital (per worker) and TFP in the baseline model. Average investment wedges are inversely related to aggregate capital. A reduction in the wedge between 2006–08 is associated with an increase in capital accumulation, while the opposite is observed in 2009–12. These two episodes are inconsistent with an explanation of investment based on technological profitability only. In the period before the crisis, aggregate TFP stagnates, while in the following years TFP recovers but capital accumulation does not.

The dashed line in Fig. 2 is a counterfactual keeping the dynamic capital distortion for each industry constant at its long run value $\overline{\theta^{K,i}}$. Capital accumulation and TFP move in the same direction. Unlike the baseline, capital accumulation slows down before the crisis and increases afterwards. This illustrates the quantitative importance of the time variation in investment wedges in capital accumulation. However, their impact on TFP over time is negligible.

In the last counterfactual we eliminate heterogeneity in the variation of capital distortion across time by forcing distortions in all industries to grow equally at the observed average rate. The dotted line in Fig. 2 reveals that heterogeneity plays a minor role in capital accumulation, but matters for TFP, as in Meza et al. (2019).

5. Credit conditions and dynamic distortions

The top panel of Table 1 shows the correlation between investment wedges and credit conditions.[7] Total credit and credit intensity (credit/value added) are negatively related to the dynamic distortion. This suggests that industries with greater access to credit are able to align their capital stocks closer to 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 financial variables.

7 Data definitions of the credit variables are provided in the online appendix A (Link).

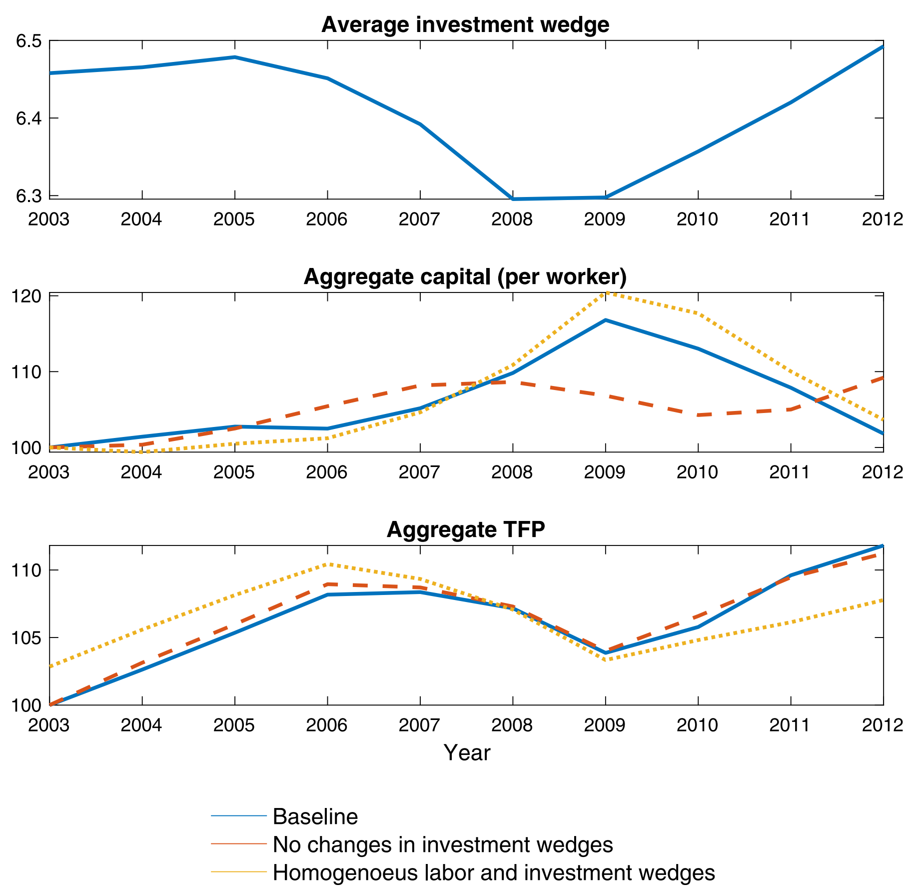

Fig. 2. Aggregate capital, TFP and average investment wedges.

Table 1
Investment wedges and credit conditions.

Correlations			
	Total credit	Credit/value added	Interest rate
$\theta_t^{K,i}$	−0.089	−0.159	0.068
$\theta^{\overline{K,i}}$	−0.097	−0.190	0.121

Regressions: Dependent variable $\theta_t^{K,i}$				
	(1)	(2)	(3)	(4)
Credit/value added	−0.738*	−0.712*		
	0.159	0.158		
Interest rate			0.187*	0.168*
			0.078	0.078
Time dummies	Yes	Yes	Yes	Yes
2-digit industry effects	No	Yes	No	Yes

Note: Standard errors below coefficients.
*Denotes significance at the 5% level.

The bottom panel of Table 1 shows the results of regressing investment wedges against credit conditions controlling for time and industry dummies, that confirm the correlation results. These results suggest that credit conditions are important determinants of the investment wedge.

6. Conclusions

We explore the role of dynamic distortions in explaining capital accumulation and TFP growth, and find that investment wedges exert a significant influence on the former, but a relatively minor one on the latter. We also show that sectors for which credit availability decreases and/or real interest rates increase experience an increase in their investment wedges. These findings highlight the importance of the banking system in financing investment for Mexican manufacturing.

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