

Credit, Misallocation and TFP: The Case of Mexico 2003-2010*

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(Preliminary and Incomplete - Do not Quote)

February 14, 2014

Abstract

We study the relation between misallocation of resources, TFP and credit conditions using sectoral data from Mexican manufacturing industries between 2003 and 2010. We use a theory-based framework to account for TFP changes in the Mexican manufacturing sector due to changes in distortions in the use of capital, labor and intermediates arising from financial frictions. We show that these distortions account for a large fraction of aggregate TFP changes in the period. We also find empirically that changes in distortions in the data are driven by changes in the availability and the cost of credit.

1 Introduction

The relationship between output growth and total factor productivity is well established. The earliest calculations of Solow (1957) attributed only 12% of the growth in the United States between 1900 and 1949 to the accumulation of factors of production, and the remaining 88% to the “residual”. Subsequent work enlarging the scope and time period of these estimates reduced the number to about 50% (see for example Klenow and Rodriguez Clare 1997), however the primacy of the contribution of TFP to growth is undeniable. Movements in TFP have played an important role in recent growth miracles in India (Bollard et. al 2013) and China (Dekle and Vandenbroucke 2010). The reverse has also been true, large drops in output during “sudden stops” have been accompanied by a large fall in TFP (Calvo 2006).¹

*We are grateful for the financial support of a grant from the Fundacion de Estudios Financieros. We also thank the Instituto Nacional de Estadística, Geografía e Informática (INEGI), and especially Gerardo Leyva and Natalia Volkow for their help with the survey on manufacturing establishments. We are indebted to the Comisión Nacional Bancaria y de Valores, especially Yearim Valles, Sirenia Vasquez and Saide Salazar for making aggregate information on bank loans available to us. Data provided to us was anonymized by the respective source. Alonso de Gortari and Hoda Nouri Khajavi provided outstanding research assistance. Any errors are our own.

¹In general the variance in output growth is more closely associated with the variance in TFP growth, rather than the variance in input use (Baier et. al 2006).

Some recent studies have highlighted the importance of input misallocation as an important factor behind these aggregate TFP changes. Pratap and Urrutia (2012) show that financial frictions can propagate interest rate shocks into measured TFP fluctuations by distorting the use of inputs in the economy. Benjamin and Meza (2009) analyze the real effects of Korea's 1997 crisis and show that a reallocation of resources towards low productivity sectors at this time generates a fall in TFP.

A recent strand of literature seeks to explain the differences in TFP levels between countries by emphasizing the role of firm-specific distortions, i.e. implicit taxes, barriers and constraints which result in the suboptimal allocation of resources and lower TFP levels (see, for instance, Restuccia and Rogerson 2008, Hsieh and Klenow 2009, Bartelsman et. al 2009). Sandleris and Wright (2011) use these same insights to understand changes in TFP over time, using firm level data from Argentina in the period around the 2001 crisis. These papers however do not investigate the reasons behind these distortions, their focus is on quantifying their effects.

The goal of this paper is to understand the role of credit and financial frictions in accounting for the misallocation of resources and the changes in TFP over time. As in Pratap and Urrutia (2012), our focus is on financial frictions distorting firms' decisions to purchase inputs. However, as in the literature reviewed in the previous paragraph, we analyze the relation between credit and distortions at the micro level, instead of the aggregate macro level. In this sense, our work relates to Buera and Moll (2011), who extend the business cycle accounting methodology to economies with heterogeneous firms and show that credit shocks and financial frictions can be mapped into measured TFP and other aggregate wedges or distortions.²

As an empirical contribution, we construct a novel data set by linking manufacturing activity in Mexico with credit flows at a disaggregated level. Our data encompasses 82 sectors of activity for the period from 2003 to 2010. This is a particularly interesting time frame to study, since it includes both the period of rapid growth of 2003-08, the economic crisis of 2008-09 and the subsequent recovery. We use this data to construct two measures of input distortions: (i) a distortion to the use of intermediate goods (ii) a distortion to the capital to output ratio. We construct a simple framework to show how these two distortions affect aggregate TFP. We also study the link between these distortions and several credit variables in our dataset, exploiting the differences in credit availability and interest rates across sectors and over time.

Our results show that deviations from the optimal use of intermediate goods and from the optimal capital labor ratio account for a substantial amount of TFP variation in this period. We also show that the amount of credit disbursed and interest rates matter for the magnitude of distortions faced by sectors, suggesting that both the availability and the cost of credit are important determinants of input use. Taken together, our results highlight an important channel through which credit affects real economic activity.³

The paper is organized as follows. In Section 2 we describe the data used to analyze the relationship between economic activity and credit and present aggregate statistics. Section 3 sets out a simple framework to link financial frictions and sectoral distortions and to account for aggregate TFP changes. In Section 4 we apply this methodology to our dataset for Mexican manufacturing and find that distortions play a large role

²Chari, Kehoe and McGrattan (2007) introduced the methodology of business cycle accounting as a way of inferring the aggregate levels of distortions that an economy faces and how they evolve over time. The idea is to infer these distortions from the wedges obtained from the optimality conditions of a standard neoclassical model. For example, the labor wedge is defined as the ratio between the marginal rate of substitution of consumption for leisure and the marginal product of labor, which should be equal in an undistorted economy.

³This is in contrast to Midrigan and Xu (2013) who find that financial frictions have small effects on misallocation of capital in South Korea. They do not consider the purchase of intermediate goods and do not use financial data to calibrate their model.

in TFP fluctuations both in the rapid growth period and in the recovery from the crisis. Finally, in Section 5 we investigate the empirical relationship between these distortions and indicators of credit using sectoral data.

2 Data and Stylized Facts

A major contribution of our paper is the construction of a data set that links manufacturing activity with bank lending to firms. In this section we describe our two main data sources and our procedure to merge them. We also describe some stylized facts for the manufacturing sector during the period 2003-10 obtained from our combined database. In particular, we show a large increase in total factor productivity (TFP) from 2004-2008, a contraction in 2009 related to the world financial crisis, and a small recovery in 2010. At the same time real short term credit to manufacturing increased during the rapid growth period, especially from 2005 to 2008, and collapsed in 2009 and 2010, with no observed recovery at the end of the period.

2.1 Dataset Construction

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 loan portfolio of all commercial banks, known as the R04C, maintained by the banking regulatory authority, the *Comision Nacional Bancaria y de Valores* (CNBV). Confidentiality restrictions prohibit us from analyzing the data at the establishment or loan level. We therefore work at the lowest level of aggregation currently feasible, namely at the 4-digit industry level, following the 2007 North American Industrial Classification System (NAICS). The banking data are at a monthly frequency, whereas the establishment level data are collected yearly. We therefore aggregate the loan data to the annual level. A further complication is that while the EIA uses the NAICS throughout the sample, the R04C data is classified according to an internal classification system for the period up to July 2009 and to the NAICS thereafter. We construct a flexible, probabilistic crosswalk between these two systems, details of which are given in the Appendix.

The EIA data is a representative sample of nearly 7000 manufacturing establishments. We were able to get data on 86 sectors at the 4-digit level and 231 subsectors at the 6-digit level.⁴ We use data on gross output and expenditure on intermediate goods to construct measures of value added. The labor input is measured as the number of people hired directly and indirectly by the establishment. The capital input is constructed using the perpetual inventory method, using information on investment from the EIA data.

The R04C dataset is the universe of loans by commercial banks to firms. This data is outstanding loan balances, collected at the loan level, and is available at a monthly 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 is collected) in a particular sector in a particular month. This gives us information on how much credit was disbursed to each sector in each period. Our measure of credit includes outstanding interest payments.⁵ We construct the stock of credit in each sector by looking at the total debt outstanding of each sector in each period, regardless of the period of disbursement. We focus on data for short term

⁴Aggregates of subsectors containing 4 or fewer firms were not provided to us in the interests of confidentiality.

⁵We also constructed a measure of credit that excludes interest payments which behaves very similarly to the other measure at the aggregate and sectoral level.

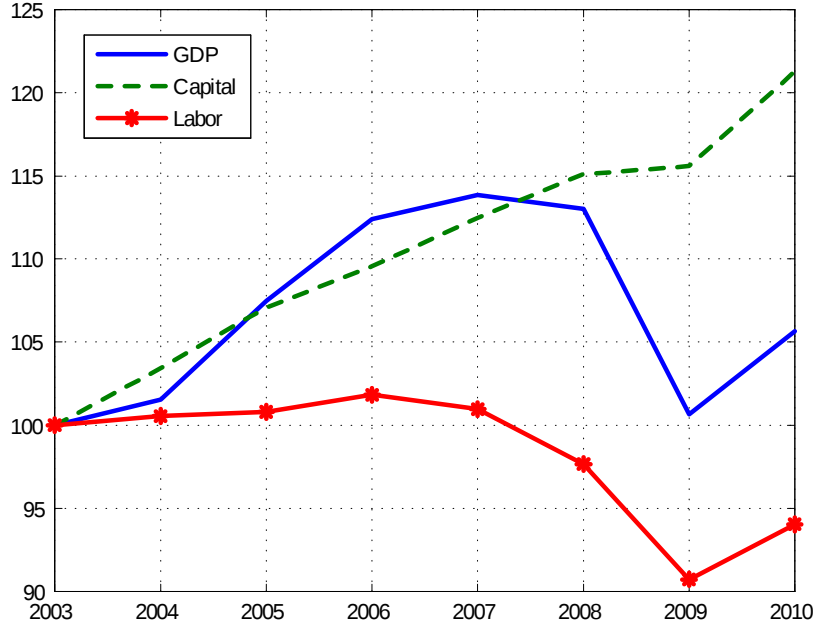


Figure 1: Aggregate GDP, Capital and Labor (2003=100)

credit. Finally, we construct cost of credit measures by looking at average and median interest rates paid by each loan, by sector, weighted by the size of the loan in total credit flow in the corresponding period.

All nominal variables, with the exception of intermediate goods are deflated by the producers price index for manufacturing published by the INEGI. Intermediate goods are deflated by an intermediate goods index.

2.2 Aggregate Stylized Facts: Output and TFP

We calculate aggregates by adding up industry level variables. We focus on 2003-2010, the period in which our two databases overlap. As mentioned earlier, this period allows us to study two phenomena: high growth in output and TFP in the first five years and a contraction in the last two periods as the international financial crisis affected the Mexican economy.

Figure 1 shows real manufacturing GDP, capital and labor inputs from our sample, relative to the year 2003. The former is calculated by adding up real value added in all sectors, whereas the inputs are the stock of capital and personnel employed aggregated over sectors. The figure illustrates the manufacturing boom between 2003 and 2008, when output grew at an annual average of 2.5%. Interestingly labor input was relatively stagnant in this period, suggesting that the sources of growth lay in productivity.⁶ This period of expansion came to an abrupt halt in 2009, when output contracted by almost 11%. This fall in output was

⁶We verified this fact by looking at employment in manufacturing in a completely different database, the National Survey of Occupation and Employment (ENOE for its acronym in Spanish). The employment series from EIA and from ENOE exhibit very similar behavior.

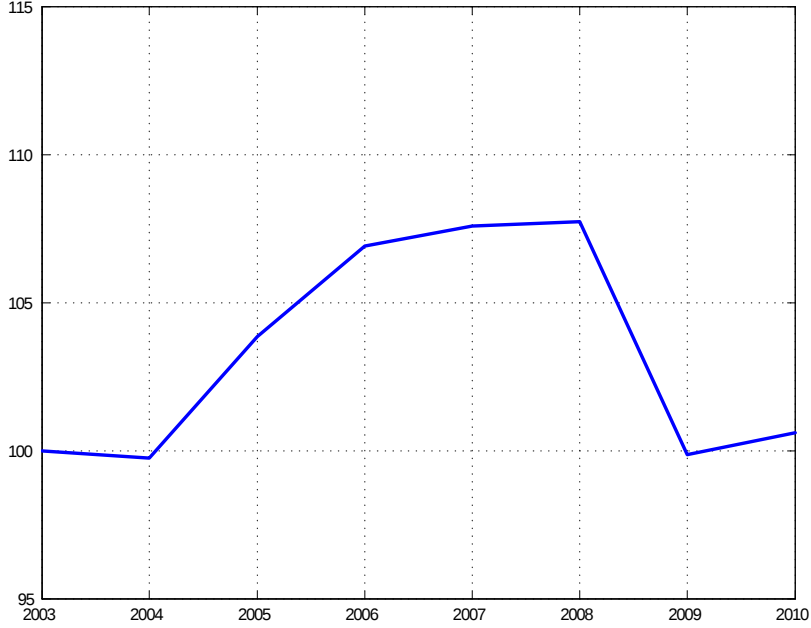


Figure 2: Total Factor Productivity (2003=100)

accompanied by a smaller drop in labor of about 7%. Investment slowed down substantially between 2008 and 2009, leading to a deceleration in the growth of capital stock. The recovery in the following year was modest, as output and labor inputs grew by less than 4%.

Figure 2 shows the evolution of aggregate total factor productivity (TFP) over the period, relative to 2008. Assuming a Cobb Douglas production function, aggregate TFP is defined as

$$A = \frac{Y}{K^\alpha L^{1-\alpha}}$$

where Y represents real value added and K and L measure aggregate inputs of capital and labor respectively. $1 - \alpha$ is constructed as a weighted average of the labor share in income of each sector.⁷ The weights are the share of each sector in total output. Figure 2 shows that TFP increased between 2004 and 2008, mirroring the increase in output. TFP fell in 2009 by 7.3% and recovered slightly in the following year. This figure shows the importance of the role of total factor productivity in output fluctuations.

2.3 Aggregate Stylized Facts: Credit Flows

Figure 3 shows the measure of short term⁸ credit flow described earlier. The aggregate flow of credit, which was declining in the first few years of the sample, increased between 2005 and 2008, and dramatically in the

⁷For reasons elaborated in the next section, these income shares are taken from the corresponding sectors in the U.S.

⁸We define short term credit as credit with a maturity of 12 months or less. As we will see in the next sections, we consider financial frictions which affect the amount of working capital to which firms have access. The data counterpart of that is short term credit.

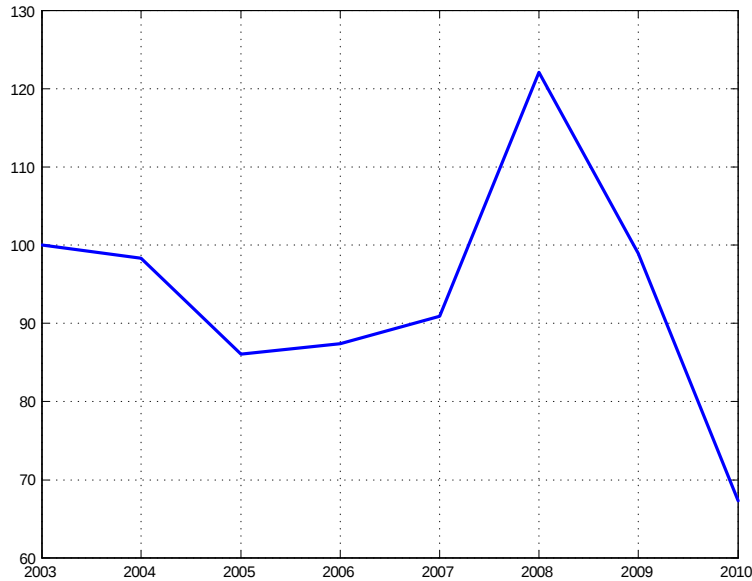


Figure 3: Real Credit Flow (2003=100)

2007-2008 period.⁹ The fall in output in 2009 was also reflected in a fall in aggregate credit. Interestingly, the recovery in aggregate output was not accompanied by a recovery in credit.

One natural question is whether these changes in credit flows reflect supply or demand factors. Probably both. Still, some evidence suggests that the supply of credit by banks has played a leading role. We look at the behavior of *credit intensity*, measured as the ratio of credit flows to gross output. As shown in Figure 4, the expansion in real credit is accompanied by an increase in credit intensity, and the credit contraction in 2009-10 also shows as a fall in this ratio. Therefore, credit did not just respond to the cyclical behavior of gross output.

The aggregate picture, while informative, obscures sectoral allocation issues. In the following section we set up a simple framework to measure distortions at the sectoral level from optimal input use and show how they relate to aggregate TFP.

3 A Simple Model of Credit, Distortions and TFP

We consider a simple, partial equilibrium model of multi-sector production with financial frictions. These frictions introduce wedges between factor prices and marginal products, that we summarize in two sector specific distortions: (i) a distortion affecting the capital to labor ratio; and (ii) a distortion affecting the ratio

⁹At this point it is important to note that, since the financial crisis of 1994, Mexico has a low degree of financial intermediation. The private credit to GDP ratio was 14% in 2003, at the beginning of our period of analysis (see Kehoe and Meza 2011). This number is much lower than in similar Latin American economies (61% in Chile, for instance). It is possible that, starting from the historical low levels of credit in Mexico, the expansion of credit might reduce misallocation, as firms had more access to credit and were possibly able to come closer to efficient levels of factor use.

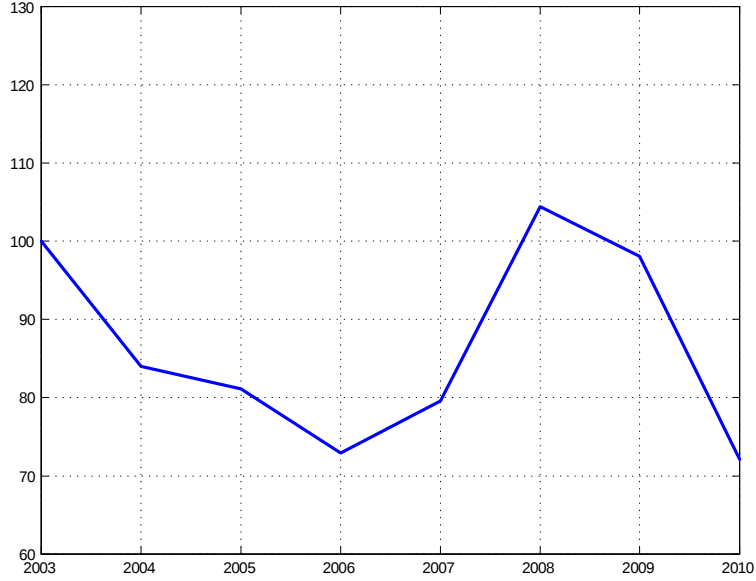


Figure 4: Credit Flow relative to Gross Output (2003=100)

of intermediate goods to output. Using this framework, we first establish a link between credit conditions and distortions. Then, we obtain an expression relating changes in aggregate TFP to the level of distortions and their growth rate. These two results will guide our empirical analysis in the following two sections.¹⁰

3.1 Production and Firm's Optimization

Manufacturing activity, which we refer to as the “aggregate” in what follows, is composed of a discrete number n of sectors. Each sector is characterized by a representative firm operating under constant returns to scale, which produces a differentiated good. Firms rent capital K and labor L and combine them with intermediate goods M to produce (gross) output, according to the production function

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

Parameter A^i is a sector specific technology parameter, possibly changing over time. Factor shares α^i and ε^i are assumed to be constant over time, but are also sector specific.

We introduce two types of financial frictions to the standard, static, firms' optimization problem: A simple working capital constraint and a borrowing limit. Firms borrow at the beginning of the period to finance a fraction κ^i of capital services and intermediates purchases. The loan is repaid at the end of the period including a sector specific interest rate, that we take as exogenous. In addition, loans for working capital are constrained to be no larger than a fraction of the value of its sales.

¹⁰In the next stage of the project we plan to embed this production structure in a general equilibrium model of the Mexican economy. Solving this model with financial frictions calibrated from the data will allow us to quantify their impact on the evolution of distortions and aggregate TFP using a more structural approach.

The problem of the firm in each sector at period t is to maximize profits

$$\begin{aligned} \max_{L_t^i, K_t^i, M_t^i} \quad & \{p_t^i Y_t^i - w_t L_t^i - (1 + \kappa^i r_t^{*i}) r_t K_t^i - (1 + \kappa^i r_t^{*i}) p_t^M M_t^i\} \\ \text{s.to.} \quad & Y_t^i = A_t^i \left[(K_t^i)^{\alpha^i} (L_t^i)^{1-\alpha^i} \right]^{\varepsilon^i} (M_t^i)^{1-\varepsilon^i} \\ & \kappa^i (r_t K_t^i + p_t^M M_t^i) \leq \frac{\xi_t^i p_t^i Y_t^i}{1 + r_t^{*i}} \end{aligned}$$

where κ^i is the sector specific fraction of capital services and intermediates purchases financed through credit. Together with the interest rate r_t^{*i} , the sequence of parameters ξ_t^i captures credit conditions by governing the tightness of the borrowing constraint. These credit conditions affect sectors differently and can change over time. For now, the sequences for factor prices (w_t , r_t , p_t^M) and sectoral output prices (p_t^i) are all exogenous.

3.2 First Order Conditions and Sectoral Distortions

Since the problem for each representative firm is static, from now on we omit the subscript t . The first order conditions for profit maximization imply

$$\begin{aligned} \theta_{K,L}^i &\equiv 1 + \kappa^i r^{*i} + \kappa^i \lambda^i = \frac{\alpha^i}{1 - \alpha^i} \left(\frac{w}{r} \right) \frac{L^i}{K^i} \\ \theta_{M,Y}^i &\equiv \frac{1 + \kappa^i r^{*i} + \kappa^i \lambda^i}{1 + \frac{\lambda^i \varepsilon^i}{1 + r^{*i}}} = (1 - \varepsilon^i) \left(\frac{p^i}{p^M} \right) \frac{Y^i}{M^i} \end{aligned} \quad (2)$$

where λ^i is the Lagrange multiplier associated to the borrowing constraint.

Each sector faces two sector-specific distortions: (i) a distortion $\theta_{K,L}^i$ affecting the capital to labor ratio; and (ii) a distortion $\theta_{M,Y}^i$ affecting the ratio of intermediate goods to output. These distortions arise because the shadow cost of credit increases the effective cost of capital relative to labor, and of intermediates relative to output, distorting the optimal mix of inputs. In a world without financial frictions these two distortions will disappear ($\theta_{K,L}^i = \theta_{M,Y}^i = 1$) and the standard first order conditions equating factor prices to marginal products would be recovered. We can also easily show that an increase in the sector specific interest rate or the borrowing constraint tightness would increase these two distortions.

From now on, we will proceed with the analysis connecting financial frictions and aggregate TFP taking these two distortions as primitives.

3.3 Distortions and Sectoral Output

We can rewrite firms' first order conditions as:

$$\frac{K^i}{L^i} = \left(\frac{\alpha^i}{1 - \alpha^i} \right) \left(\frac{w}{r} \right) \frac{1}{\theta_{K,L}^i} \quad \frac{M^i}{Y^i} = (1 - \varepsilon^i) \left(\frac{p^i}{p^M} \right) \frac{1}{\theta_{M,Y}^i}$$

so that

$$Y^i = (A^i)^{\frac{1}{\varepsilon^i}} \left[\left(\frac{\alpha^i}{1 - \alpha^i} \right) \left(\frac{w}{r} \right) \frac{1}{\theta_{K,L}^i} \right]^{\alpha^i} \left[(1 - \varepsilon^i) \left(\frac{p^i}{p^M} \right) \frac{1}{\theta_{M,Y}^i} \right]^{\frac{1 - \varepsilon^i}{\varepsilon^i}} L^i.$$

In growth rates

$$\widetilde{K}^i = \widetilde{L}^i - \widetilde{\theta_{K,L}^i} \quad \widetilde{M}^i = \widetilde{Y}^i - \widetilde{\theta_{M,Y}^i} \quad (3)$$

where $\widetilde{x}_t = \log\left(\frac{x_t}{x_0}\right) \approx \frac{x_t - x_0}{x_0}$. This implies

$$\widetilde{Y}^i = \left(\frac{1}{\varepsilon^i}\right) \widetilde{A}^i - \alpha^i \widetilde{\theta}_{K,L}^i - \left(\frac{1 - \varepsilon^i}{\varepsilon^i}\right) \widetilde{\theta}_{M,Y}^i + \widetilde{L}^i \quad (4)$$

assuming that factor shares *and* relative prices remain constant over time. This expression allows us to decompose changes in sectoral output into changes in technology, changes in the two distortions and changes in employment.

3.4 Aggregating Sectors

We define aggregate output (at constant prices) as the sum across sectors of the value of output:

$$Y \equiv \sum_{i=1}^n p_0^i Y^i$$

and, similarly, aggregate inputs as

$$K \equiv \sum_{i=1}^n K^i \quad L \equiv \sum_{i=1}^n L^i \quad M \equiv \sum_{i=1}^n M^i.$$

We also define (value-added) aggregate total factor productivity as

$$TFP \equiv \frac{Y - p_0^M M}{K^\alpha L^{1-\alpha}}$$

using as the aggregate share of capital an output-weighted average of the sectoral shares

$$\alpha = \sum_{i=1}^n \left(\frac{p_0^i Y_0^i}{Y_0}\right) \alpha^i.$$

In growth rates,

$$\widetilde{TFP} = \left(\frac{Y_0}{Y_0 - p_0^M M_0}\right) \widetilde{Y} - \left(\frac{p_0^M M_0}{Y_0 - p_0^M M_0}\right) \widetilde{M} - \alpha \widetilde{K} - (1 - \alpha) \widetilde{L}$$

assuming again that factor shares and relative prices remain constant over time. Therefore,

$$\widetilde{TFP} = \sum_{i=1}^n \left[\left(\frac{p_0^i Y_0^i}{Y_0 - p_0^M M_0}\right) \widetilde{Y}^i - \left(\frac{p_0^M M_0^i}{Y_0 - p_0^M M_0}\right) \widetilde{M}^i - \alpha \left(\frac{K_0^i}{K_0}\right) \widetilde{K}^i - (1 - \alpha) \left(\frac{L_0^i}{L_0}\right) \widetilde{L}^i \right]$$

or, replacing (3) and (4),

$$\begin{aligned} \widetilde{TFP} = \sum_{i=1}^n & \left\{ \omega^i \left(\frac{1}{\varepsilon^i}\right) \left(\widetilde{A}^i\right) + \left[\omega^i - \alpha \left(\frac{K_0^i}{K_0}\right) - (1 - \alpha) \left(\frac{L_0^i}{L_0}\right) \right] \widetilde{L}^i \right. \\ & \left. + \left[\frac{p_0^M M_0^i}{Y_0 - p_0^M M_0} - \omega^i \left(\frac{1 - \varepsilon^i}{\varepsilon^i}\right) \right] \widetilde{\theta}_{M,Y}^i + \left[\alpha \left(\frac{K_0^i}{K_0}\right) - \omega^i \alpha^i \right] \widetilde{\theta}_{K,L}^i \right\} \end{aligned} \quad (5)$$

with $\omega^i \equiv \frac{p_0^i Y_0^i - p_0^M M_0^i}{Y_0 - p_0^M M_0}$ representing the share of value added of sector i in the aggregate. Now, let's define the initial level of aggregate distortions to the capital to labor ratio as

$$\theta_{K,L} \equiv \frac{\alpha}{1 - \alpha} \left(\frac{w_0}{r_0}\right) \frac{L_0}{K_0}$$

and the ratio between the initial aggregate and firm specific labor shares of income in the data

$$\Phi^i \equiv \frac{(1 - \alpha) (Y_0 - p_0^M M_0) / w_0 L_0}{(1 - \alpha^i) \varepsilon^i p_0^i Y_0^i / w_0 L_0^i}.$$

Notice that this ratio is one if there are no distortions. Using these definitions and the definitions of sectoral distortions, we can finally write

$$\begin{aligned} \widetilde{TFP} = \sum_{i=1}^n \omega^i & \left\{ \left(\frac{1}{\varepsilon^i} \right) (\widetilde{A}^i) + \left[1 - \Phi^i \left(\frac{\varepsilon^i \theta_{M,Y}^i}{\theta_{M,Y}^i - (1 - \varepsilon^i)} \right) \left(\alpha^i \frac{\theta_{K,L}}{\theta_{K,L}^i} - (1 - \alpha^i) \right) \right] \widetilde{L}^i \right. \\ & \left. + (1 - \varepsilon^i) \left[\frac{1}{\theta_{M,Y}^i - (1 - \varepsilon^i)} - \frac{1}{\varepsilon^i} \right] \widetilde{\theta_{M,Y}^i} + \alpha^i \left[\Phi^i \left(\frac{\varepsilon^i \theta_{M,Y}^i}{\theta_{M,Y}^i - (1 - \varepsilon^i)} \right) \frac{\theta_{K,L}}{\theta_{K,L}^i} - 1 \right] \widetilde{\theta_{K,L}^i} \right\} \quad (6) \end{aligned}$$

3.5 Decomposing TFP changes

The resulting expression (6) decomposes aggregate TFP changes in four components:

- Changes in sectoral technologies¹¹:

$$\sum_{i=1}^n \omega^i \left(\frac{1}{\varepsilon^i} \right) \widetilde{A}^i$$

- Reallocation of labor across sectors:

$$\sum_{i=1}^n \omega^i \left[1 - \Phi^i \left(\frac{\varepsilon^i \theta_{M,Y}^i}{\theta_{M,Y}^i - (1 - \varepsilon^i)} \right) \left(\alpha^i \frac{\theta_{K,L}}{\theta_{K,L}^i} - (1 - \alpha^i) \right) \right] \widetilde{L}^i$$

This component is zero if there is no labor reallocation ($\widetilde{L}^i = 0$) or if there is no initial distortions ($\theta_{K,L} = \theta_{K,L}^i = \theta_{M,Y}^i = 1$) and the labor shares are "correct" ($\Phi^i = 1$). Also, for $\theta_{M,Y}^i = 1$, labor reallocation towards a sector i with a high capital to labor ratio distortion with respect to the average ($\theta_{K,L}^i > \theta_{K,L}$) would increase aggregate TFP.¹² Similarly, for $\theta_{K,L}^i = \theta_{K,L}$, reallocation of labor towards sectors with relatively high intermediates to output distortions ($\theta_{M,Y}^i = 1$) would increase aggregate TFP.

- Changes in sectoral distortions to the intermediates to output ratio:

$$\sum_{i=1}^n \omega^i (1 - \varepsilon^i) \left[\frac{1}{\theta_{M,Y}^i - (1 - \varepsilon^i)} - \frac{1}{\varepsilon^i} \right] \widetilde{\theta_{M,Y}^i}$$

This component is zero if there is no change in the distortions ($\widetilde{\theta_{M,Y}^i} = 0$) or if there are no initial distortions ($\theta_{M,Y}^i = 1$). An increase in $\theta_{M,Y}^i$ reduces aggregate TFP if and only if the initial distortion is relatively high in this sector ($\theta_{M,Y}^i > 1$), this is, if it increases the disparity in distortions across sectors.

- Changes in sectoral distortions to the capital to labor ratio:

$$\sum_{i=1}^n \omega^i \alpha^i \left[\Phi^i \left(\frac{\varepsilon^i \theta_{M,Y}^i}{\theta_{M,Y}^i - (1 - \varepsilon^i)} \right) \frac{\theta_{K,L}}{\theta_{K,L}^i} - 1 \right] \widetilde{\theta_{K,L}^i}$$

¹¹This component would be also a function of the distribution of *firm-level* distortions, which we are omitting in this first analysis.

¹²Notice that sectors with high distortions to the capital to output ratio exhibit a high marginal product of capital, so the type of reallocation that reduces aggregate TFP is one that moves resources from low to high marginal products of capital sectors.

This component is zero if there is no change in the distortions ($\widetilde{\theta_{K,L}^i} = 0$) or if there are no initial distortions ($\theta_{M,Y}^i = \theta_{K,L}^i = \theta_{K,L} = 1$). Again, for $\Phi^i = \theta_{M,Y}^i = 1$, an increase in $\theta_{K,L}^i$ reduces aggregate TFP if and only if the initial distortion is relatively high in this sector ($\theta_{K,L}^i > \theta_{K,L}$).

4 Data Analysis: From Distortions to TFP

In the first step of our empirical analysis we take the two distortions obtained in the previous section as primitives and use the establishment level data from the EIA to measure them. The data is annual and aggregated to the 4 digit NAICS classification. Once we exclude sectors with missing information, we have a total of 82 sectors within Manufacturing. Each of these sectors is mapped into a sector in the model (so $n = 82$).

The result is a panel of sectoral distortions and other variables for the 2003-10 period, whose statistical properties we report. Using this information, we perform the accounting exercise following the decomposition in equations (5) and (6) to assess the quantitative contribution of sectoral distortions to aggregate TFP changes. The results show that the components associated to distortions account for a large fraction of the variation of aggregate TFP over time.

4.1 Measuring Distortions

For each sector, we have data on gross output, employment, the wage bill, intermediate goods purchased, investment and depreciation. Except for employment, all these variables are measured at current prices. When necessary, we use an aggregate PPI for manufacturing (to deflate gross output, capital and investment) and an aggregate index for the price of intermediate goods to deflate the purchase of intermediates.¹³ To construct our measure of the capital stock we use the perpetual inventory method. We use initial investment and a steady-state assumption to calculate the initial capital stock. We then update the capital stock using investment flows and a sector specific depreciation rate.

The construction of our measure of distortions follows the formulas in (2). Notice that since factor shares are not independent of distortions, we cannot identify the production function coefficients with these shares. Our strategy is to take the factor shares from the corresponding sectors i the U.S., as an example of an undistorted economy. For each sector i and at each period t , distortions are then computed as:

$$\theta_{(K,L),t}^i = \frac{\alpha^{i,us}}{1 - \alpha^{i,us}} \left(\frac{\text{nominal wage bill}_t^i}{0.14 \times \text{nominal capital stock}_t^i} \right)$$

assuming a 14% rate of return (obtained of the sum of the average real interest rate on loans and the average depreciation rate) and

$$\theta_{(M,Y),t}^i = (1 - \varepsilon^{i,us}) \left(\frac{\text{nominal gross output}_t^i}{\text{nominal intermediates purchases}_t^i} \right).$$

¹³Ideally, we would like to use sector specific deflators for output and capital goods deflators for capital stock, but the lack of sufficiently disaggregated price indices prevents us from doing so.

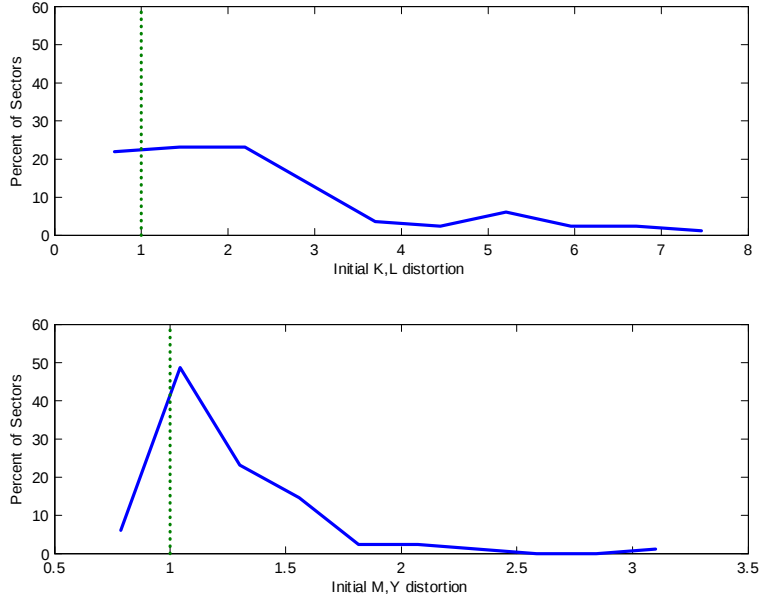


Figure 5: Initial Distribution of Distortions (2003)

The production function (1) allows us to compute the sectoral technology level A_t^i as

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

where all variables (except employment) are deflated as described above. Aggregation of sectors is performed as in subsection 1.2.

4.2 Sectoral Distributions

Figure 5 plots the histogram for each type of distortions in the initial year. The intermediates distortions exhibit a large mass of sectors around the level of one (no distortion) and a fat right tail, indicating a majority of sectors with distortions that *reduce* intermediates to output ratios. The capital-labor distortion is more uniformly distributed, with a large majority of sectors (about 80 percent) with distortions that reduce the capital to labor ratios.

Figures 6 and 7 plot the histograms for the *changes* in the two types of distortions, in the subperiods 2003-08 and 2009-10. As observed, most sectors reduced their levels of distortions in the period previous to the crisis, although there is substantial heterogeneity across sectors. In the crisis period the distribution of changes shifts to the right, towards more sectors increasing their level of distortions or reducing them at a slower pace.

An alternative characterization of the distributions of distortions is provided as a set of summary statistics in Table 1. The data shows a decrease in the average level of both levels of distortions over time, although the decline is more marked for $\theta_{K,L}$ than for $\theta_{M,Y}$. However, the dispersion of these distortions

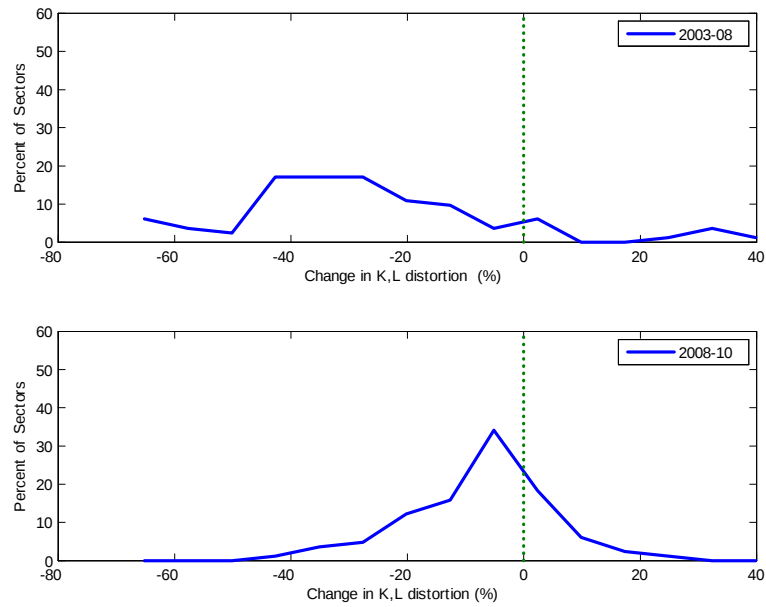


Figure 6: Distribution of Changes in Capital-Labor Distortions

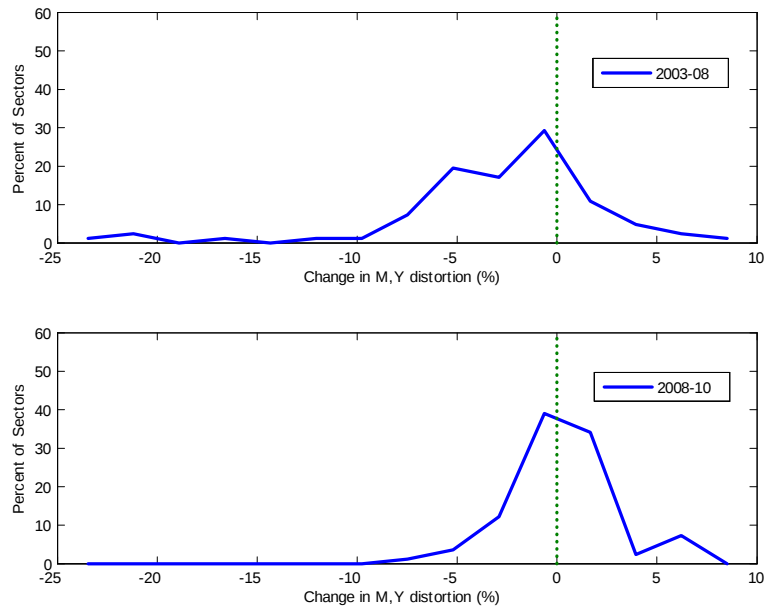


Figure 7: Distribution of Changes in Intermediates Distortions

	2003-04	2005-06	2007-08	2009-10
Average $\theta_{K,L}$	2.52	2.13	1.78	1.52
Std/Mean $\theta_{K,L}$	0.69	0.74	0.77	0.75
Correl ($\theta_{K,L}, L$)	-0.01	-0.02	-0.01	0.04
Correl ($\theta_{K,L}, A$)	0.20	0.14	0.13	0.20
Average $\theta_{M,Y}$	1.24	1.22	1.21	1.21
Std/Mean $\theta_{M,Y}$	0.30	0.30	0.30	0.31
Correl ($\theta_{M,Y}, L$)	0.16	0.17	0.17	0.16
Correl ($\theta_{M,Y}, A$)	0.20	0.21	0.31	0.37
Correl ($\theta_{K,L}, \theta_{M,Y}$)	0.13	0.17	0.19	0.23

Table 1: Descriptive Statistics for Sectoral Distortions in Mexico’s Manufacturing

(yearly % changes)	2003-06	2006-08	2008-09	2009-10
TFP growth	2.25	0.39	-7.30	0.73
due to technology	1.09	-0.17	-10.6	0.05
(a) due to reallocation	-0.01	0.53	0.99	-0.54
(b) due to $\theta_{K,L}$	0.28	0.52	-0.41	1.25
(c) due to $\theta_{M,Y}$	0.73	0.48	0.12	0.66
(a) + (b) + (c)	1.00	1.53	0.70	1.37
residual	0.15	-0.97	2.58	-0.69

Table 2: TFP Growth Decomposition

across sectors increase in the latest period, associated with the crisis. The distortions seem to be correlated with sectoral productivity, suggesting that more productive firms are constrained in their use of inputs.

4.3 Distortions and Aggregate TFP

Table 2 reports the results of the decomposition of aggregate TFP growth for several periods. The residual is computed as the actual TFP growth minus the predicted TFP growth due to the four factors mentioned before, according to equations (5) and (6). Omitted factors such as changes in relative prices and factor shares, as well as errors in the approximation, would be included in this residual.¹⁴

As expected, sectoral technologies account for a large fraction of aggregate TFP growth, even if we subtract the residual from it (about 40 percent during the growth period of 2003-06, and almost all of the drop of TFP during the 2009 crisis). However, a remarkable finding is that changes in sectoral distortions account also for a significant fraction of aggregate TFP growth. During the growth period, the combined effect of both distortions is as large as the component attributed to technology. A systematic decrease in the levels of distortions is partly responsible for the productivity gains in that period, combined with a reallocation of labor towards sectors with lower levels of distortions. The contribution of distortions to the

¹⁴As a check the robustness of the results, we repeated the exercise from the previous subsection using a more disaggregated sample from Mexican manufacturing (EIA), at the 6-digit NAICS level. This sample allows us to increase the number of sectors from 82 to 215. The results of the TFP growth decomposition are almost identical.

TFP drop during the crisis is small. However, the recovery of 2010 seems to be driven almost entirely by changes in sector specific distortions.

5 Data Analysis: From Credit Conditions to Distortions

As the previous section demonstrates, sector specific distortions play a large role in TFP fluctuations. In the second step of our analysis we investigate the empirical relationship between these distortions and indicators of credit. In particular, we test for the predictions of the model with respect to the impact of changes in credit availability and interest rates in the two distortions, separately.

We use firm level loan data aggregated to the 4 digit sector level and match to the data on distortions at the same level of aggregation. As a measure of credit, we use the short term flow of credit to the sector inclusive of interest liabilities.¹⁵ We measure interest rates as the interest rate on the median loan in the sector in the current year.¹⁶

5.1 Distortions in the Intermediates to Output Ratio

Table 3 shows the results for the distortions on intermediate goods. Each row of the table represents a series of regressions, each with the independent variable in the left hand side column. The first three columns show a simple OLS with time dummies, while the next three show fixed effects regressions. Columns (7) to (9) show fixed effects augmented with time effects and the last three columns show regressions of each variable interacted with time dummies. For brevity, only the interactions for the 2008-2010 period are shown. Heteroscedasticity consistent standard errors are given below the estimates.

The first panel shows regressions with the credit to output ratios, where the denominator is obtained from the sectoral data of the EIA, while the next two panels are the regressions with measures of credit flow and interest rates respectively. In each case we also present estimates with additional controls for sector size or productivity.

Columns (1) to (3) of Panel A shows that credit intensity and $\theta_{M,Y}$ are negatively related. This seems to suggest that the use of credit is an important source of minimizing input distortions. Concerns about the endogeneity of credit intensity could arise if more productive sectors, or sectors with larger collateral have smaller distortions to input use and also have more access to credit. However, as columns (2) and (3) show, our results are robust to the inclusion of additional controls such as capital stock or sectoral productivity. Interestingly, more productive sectors also have larger distortions, suggesting that the removal of these distortions would have large effects on output.

Columns (4) to (6) and (10) to (12) show that we still have estimates with the right sign if we include sectoral heterogeneity and time varying coefficients. In many cases the coefficient is not significant, but given that the numerator and the denominator of the credit to output ratio come from different sources, we expect a certain degree of variability, reflected in the large standard errors.

¹⁵As mentioned earlier, short term credit refers to credit issued for a term of 12 months or less. We also use an alternative measure of short term credit net of interest liabilities with almost identical results.

¹⁶We also used an alternative measure of interest rate which is the average interest rate, weighted by the size of the loan. However, this measure is likely to be biased downwards since larger loans are associated with lower interest rates in the data.

Table 3: The Intermediate Goods Distortion

Panel A:	Dependent Variable $\theta_{M,Y}^i$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Credit/Output	-0.1024** 0.0529	-0.0928* 0.0512	-0.0885* 0.0536	-0.001 0.0105	0.0003 0.0104	-0.0009 0.0104	0.0023 0.0102	0.0029 0.0101	0.0022 0.0102	-0.0145 0.0132 -0.0024 0.013 -0.0101 0.0146	-0.0144 0.0131 -0.0001 0.0128 -0.008 0.0144	-0.0144 0.0132 -0.0023 0.0129 -0.0098 0.0145 -0.1674** 0.0786
Capital			0.1245* 0.0802			-0.2011 [†] 0.0804			-0.05 0.0792			
A		0.3808 [†] 0.0564			0.0697 [†] 0.0181			0.0618 [†] 0.0175			0.0657 [†] 0.0177	
Panel B:												
Credit Flow	0.0116 [†] 0.0032	0.0088 [†] 0.0031	0.0111 [†] 0.0036	-0.0012* 0.0008	-0.0012* 0.0007	-0.0012* 0.0008	-0.0011* 0.0007	-0.0011* 0.0007	-0.0011* 0.0007			
Credit Flow										-0.0018** 0.0008 -0.0011 0.0012 -0.0029** 0.0014	-0.0018** 0.0008 -0.001 0.0012 -0.0027** 0.0014	-0.0018** 0.0008 -0.0011 0.0012 -0.0028** 0.0014 -0.0521 0.0825
Capital			0.0227 0.0881			-0.2005 [†] 0.0802			-0.0501 0.079		0.0649 [†] 0.0177	
A		0.3614 [†] 0.0567			0.0699 [†] 0.0181			0.062 [†] 0.0175				
Panel C:												
Interest Rate	0.038 [†] 0.0091	0.0332 [†] 0.0088	0.0383 [†] 0.009	-0.0018 [†] 0.0005	-0.0019 [†] 0.0005	-0.0018 [†] 0.0005	0.0002 0.0013	0.0005 0.0013	0.0002 0.0013			
Interest Rate										0.0001 0.0014 0.0005 0.0016 0.0002 0.0017	0.0003 0.0014 0.001 0.0016 0.0007 0.0017	0.0001 0.0014 0.0005 0.0016 0.0002 0.0017
Capital			0.1549** 0.0782			-0.1952 [†] 0.07962			-0.048 0.0791			
A		0.3674 [†] 0.0561			0.074 [†] 0.018			0.0621 [†] 0.0175			0.0603 [†] 0.0176	
Sector Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Note: * $p < 0.15$, ** $p < 0.05$, [†] $p < 0.01$ Heteroscedasticity consistent standard errors below.

Table 4: The Capital Labor Distortion

Panel A:	Dependent Variable $\theta_{K,L}^i$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Credit/Output	-0.3536 0.2899	-0.3198 0.2863	-0.5556* 0.2905	-0.4665** 0.2024	-0.4243** 0.1958	-0.4637** 0.2008	-0.0886 0.1625	-0.0747 0.1588	-0.0867 0.1626	-0.368* 0.2382 -0.7091 [†] 0.2335 -0.5487** 0.2623	-0.3657* 0.2307 -0.6416 [†] 0.2264 -0.4881** 0.2542	-0.3661* 0.237 -0.7062 [†] 0.2323 -0.5416** 0.261
Credit/Output												
Capital			-1.8042 [†] 0.4346			-4.9967 [†] 1.5466			1.0507 1.2608			-3.6719 [†] 1.4115
A		1.333 [†] 0.3154			2.2033 [†] 0.3429			1.4612 [†] 0.2754			1.9348 [†] 0.313	
Panel B:												
Credit Flow	-0.0789 [†] 0.0173	-0.0909 [†] 0.0171	-0.0609 [†] 0.0193	-0.0108 0.0148	-0.0114 0.0143	-0.0105 0.0147	0.0002 0.0117	-0.0003 0.0114	0.0002 0.0117	-0.0233* 0.0159 -0.0667 [†] 0.0228 -0.0868 [†] 0.0275	-0.0237* 0.0154 -0.0613 [†] 0.0221 -0.0804 [†] 0.0267	-0.0224 0.0159 -0.0653 [†] 0.0229 -0.0846 [†] 0.0275
Credit Flow												
Capital			-0.9875** 0.4773			-5.007 [†] 1.553			1.0599 1.261			-1.832 1.5859
A		1.5729 [†] 0.3119			2.2302 [†] 0.344			1.4634 [†] 0.2754			2.0507 [†] 0.3326	
Panel C:												
Interest Rate	0.1885 [†] 0.0494	0.1721 [†] 0.049	0.1845 [†] 0.0489	0.0111 0.0106	0.0069 0.0103	0.0119 0.0105	0.0259 0.0207	0.0333* 0.0202	0.0258 0.0207	-0.0002 0.022 -0.0519** 0.0253 -0.0339 0.0272	0.0042 0.0216 -0.0389* 0.0249 -0.0225 0.0268	-0.0001 0.022 -0.0519** 0.0253 -0.0345 0.0273
Interest Rate												
Capital			-1.6078 [†] 0.4231			-5.0518 [†] 1.5332			0.9546 1.2432			0.6672 1.2621
A		1.274 [†] 0.3119			2.2015 [†] 0.3404			1.4962 [†] 0.2715			1.3923 [†] 0.2777	
Sector Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Note: * $p < 0.15$, ** $p < 0.05$, [†] $p < 0.01$. Heteroscedasticity consistent standard errors below.

Panel B studies the effects of actual short term credit flow in the period. While the coefficient is positive when we don't include sectoral effects (Columns (1) to (3)), it is negative once sectoral heterogeneity is taken into account. In the last three columns, where we consider time varying coefficients, we find that the availability of credit matters for the size of the distortions in both the crisis and the recovery years. Sectors which were able to secure credit were able to bring their intermediate goods usage closer to the optimal level.¹⁷ In all cases, results are robust to additional controls of productivity and capital stock.

Finally, panel C considers the cost of the credit, as measured by the median interest rate on short term credit in the sector. The first three columns show that this is positively and significantly related to the distortion, suggesting that higher interest rates prevent firms from using their optimal input mix. The estimates remain positive when we introduce sectoral heterogeneity (Columns (7) through (9)) but they are no longer significant. The last three columns show that while the coefficient was positive even in the crisis and recovery years, it is not significant. One concern here of course is how to create a representative interest rate for a group of loans in a sector. We have experimented with alternate interest rate measures such as averages of the interest rates on all short term loans in the period, weighted by loan size, but this measure has the drawback that it may over-represent low interest loans and be biased downwards. We also plan to experiment with averages weighted by loan maturity in further research.

5.2 Distortions in the Capital Labor Ratio

Table 4 shows the relationship between the capital labor distortion and indicators of credit intensity, availability and cost. The table is organized in a similar fashion as Table 3. In general, panel A shows that sectors with a greater capital intensity have lower distortions. In particular, the last three columns of this panel indicate that greater credit intensity in the crisis and recovery implied that firms could get closer to their undistorted optimal capital labor ratio. As in the previous estimations, more productive sectors have bigger distortions in their capital labor ratio. The role of sector size, as measured by its capital stock is not conclusive, since the sign of the coefficient on capital changes across specifications,

The relationship between distortions and credit flow is presented in panel B. The negative relation between these two indicates that financial constraints are an important factor underlying distortions. As columns (10) to (12) show, the availability of credit was particularly important in the recovery from the crisis. In other words, sectors with greater availability of credit were able to reduce their input distortions during the crisis. Given the contribution of the distortions to aggregate TFP, as evidenced in table 2 this result points to the relationship between financial frictions and TFP, through the effect of the former on input allocation.

Finally the lowest panel shows the effect of interest rates on the capital labor distortion. An increase in the cost of borrowing is associated with an increase in distortions and is significant in several cases. However, the cost of credit as measured by the median interest rate in the sector does not seem to play an important role in the recovery, suggesting that it was the availability of credit, rather than its cost, which was important in reducing distortions. As mentioned earlier, it is probably worth experimenting with alternative measures of the cost of credit to establish the robustness of these results. It may also be that credit rationing occurs

¹⁷Column (10)-(12) in all tables is estimated with a full set of interactions (2003-2010) but only the last three years are shown for compactness. None of the interactions in the previous years are significant. Time varying coefficients were estimated for all other independent variables but yielded no results of interest. All results available on request from authors.

by quantity, not price, in the market for loans and so the cost of credit is not as important as its availability.

5.3 In Summary

The two sets of estimates in tables 3 and 4 taken together, highlight the role of credit in explaining the distortions on input use. Both the flow of credit and the credit intensity are negatively related to the size of distortions in the optimal use of intermediates and the capital labor ratio. As mentioned earlier, we have already seen the importance of these distortions in explaining aggregate TFP. While that was an informative accounting exercise, the estimates presented in this section give some content to what lies behind the distortions. Our results suggest that the amount of credit available to the sector is an important determinant of its ability to achieve its best input mix.

We also find that credit plays an especially important role in the recovery of the economy from the 2008 crisis. This is noteworthy because this recovery takes place without a corresponding increase in aggregate real credit and aggregate credit intensity, as shown by Figure 3. Our results therefore shed light on an important puzzle in economics, i.e. the phenomenon of “creditless recoveries”. As Calvo et. al. (2006) document, output in many emerging economies recovered after financial crises without a corresponding recovery in credit. However, our estimates show that recoveries can take place as long as credit goes to sectors that can reduce their distortions, regardless of the aggregate level of credit.

6 Conclusions

Several studies have analyzed the role of firm-specific distortions in the use of capital, labor and intermediates in accounting for differences in total factor productivity across countries. We focus instead on the impact of changes in these type of distortions in the evolution of TFP over time. Using data for Mexican manufacturing industries, we show that distortions account for a large fraction of aggregate TFP changes between 2003 and 2010. Moreover, merging the manufacturing survey with data on bank loans, we show a relation between changes in distortions and changes in the availability and the cost of credit. Taken together, the results suggest a connection between credit conditions and productivity channeled through the choice of the inputs mix by firms.

It is worth highlighting that our analysis is conducted at the sectoral level, not at the firm level. Our unit of analysis is a narrowly defined sector within manufacturing, modelled as a representative firm operating a constant returns to scale technology. Hence, in contrast with most of the literature on idiosyncratic distortions and TFP, we abstract from differences in distortions among firms within the same sector. This is arguably a limitation of our analysis driven by the data availability. However, it also helps us to focus on the sectoral margin and isolate the impact of distortions on the optimal input mix from issues related with the optimal size of firms. Our results show the quantitative importance of this margin.

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7 Appendix

7.1 Crosswalk between INEGI AND CNBV data

The sector of economic activity in the loan level data 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 where it was reclassified once the classification system changed between June and July 2009.

We build a crosswalk by observing the reclassifications that actually took place in the data. The reason for building the crosswalk in this way instead of in a more arbitrary manner is that here we can take into account what actually happened and, in some sense, try to extract the crosswalk that was used when the reclassification was made and which is not available to us.

There are 1066 categories in the R04 data while there are 598 categories at the 5-digit level in the NAICS 2007 data. This means that in order to do a complete mapping, several R04C categories might be mapped into the same NAICS 2007 category. An additional problem is that the crosswalk we observe from the data is not deterministic in the sense that each credit in the R04C is not always reclassified to the same NAICS 2007 category, rather the credits in each R04C category are reclassified into a small subset of NAICS 2007 categories (and to some more often than to others). Given this second problem we built a probabilistic crosswalk which lets us know into which categories we have to reclassify each R04C category and also tells us exactly how much we have to put into each.

As a brief illustrative example suppose we want to know how to reclassify the data from category 100000 in the R04C to the NAICS 2007. Suppose that in the disaggregated data we have 10 different credits classified to category 100000 between January and June 2009. Next suppose we see that once the reclassification takes place, we observe that 5 of these credits were reclassified during July and December 2009 into NAICS 2007 category 11111, 4 were reclassified to category 11112 and only 1 was reclassified into 11113. Then, the crosswalk would tell us that the data in category 100000 of the R04C should be distributed among categories 11111, 11112 and 11113 of the NAICS 2007 and the weights should be 50%, 40% and 10% respectively.

As mentioned previously the R04C data has 1066 categories, but when building the probabilistic crosswalk we were only able to map 995 of them. The remaining 71 categories were not mapped in this way because there were no credit observations in the disaggregated data that were originally classified into these categories and then reclassified to another in the NAICS 2007 (this happens if we have no credit observations for one of the 71 categories at all or if we only have them for the period January-June 2009). Fortunately we were able to use the catalog of the R04C to match 32 of the missing 71 categories into the NAICS 2007. To do this we matched them to the category whose name seemed more appropriate. For these 32 categories the

crosswalk is deterministic as they were assigned fully to a single NAICS 2007 category. The remaining 39 categories in the R04 were not matched because they are missing in the catalog and thus cannot be mapped in this way either.

7.2 EIA Data

Data definitions for the real variables are given below:

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.

Capital Stock is constructed using the perpetual inventory method. We use initial investment and a steady-state assumption to calculate the initial capital stock. We then update the capital stock using investment flows and a sector specific depreciation rate.

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.

Value Added is computed as gross output less intermediate goods. The former is deflated using the manufacturing PPI and the latter using the intermediate goods deflator.