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Abstract

Using a rich dataset of Colombian manufacturing establishments, we illustrate scarring effects of recessions operating through inefficient exit induced by heterogeneous credit constraints. We show that financially constrained businesses may be forced to exit the market during recessions even if they are more productive than surviving unconstrained counterparts: an unconstrained plant with TFP at the lowest 10th percentile faces the same estimated exit probability as a constrained plant with TFP at the 79th percentile. If credit constraints affect 1/3 of businesses, we estimate aggregate TFP losses of 1.2 log points after a four year long recession.

Key words: Plant exit, credit constraints, business cycles, recessions.

JEL Codes: G14, E 32, L25, O4

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Restricciones crediticias y recesiones que dejan cicatriz: evidencia a partir de establecimientos manufactureros en Colombia

Marcela Eslava, Arturo Galindo,

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Resumen

Este paper ilustra cicatrices de largo plazo de las recesiones, derivadas de la pérdida ineficiente de firmas relativamente productivas como efecto de imperfecciones en el mercado crediticio. En particular, en un ambiente con heterogeneidad en el acceso a crédito mostramos que las firmas con menor acceso a crédito pueden verse forzadas a abandonar el mercado aún si son más productivas que otras firmas con mejor acceso a crédito que sí logran sobrevivir, y que este fenómeno es significativo en recesiones. Una cuantificación de los efectos de este mecanismo sobre la productividad agregada muestra pérdidas potencialmente cuantiosas. Suponiendo que 1/3 de establecimientos en la Encuestas Anual Manufacturera de Colombia enfrenta restricciones crediticias, encontramos que un establecimiento restringido en el percentil 10 de productividad tiene la misma probabilidad de salida que uno sin restricciones crediticias en el percentil 79 de productividad. Luego de cuatro años de recesión como la vivida al final del siglo XX en Colombia, el mecanismo implicaría pérdidas de productividad de 1.2 puntos logarítmicos.

Palabras clave: salida de plantas, restricciones crediticias, ciclos, recesiones.

Clasificación JEL: G14, L25, O47.

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1 Introduction

The recent global financial crisis brought back to town concerns about the long run effects of recessions. An abundant body of literature documenting macro trends has pointed at long-lived decreases in output and employment following crises. Financial crises seem to leave particularly deep scars. But, these findings are at odds with a long held view in the theory of firm dynamics, according to which recessions are times of "cleansing": the economy gets rid of inefficient businesses, leading to gains in aggregate productivity. What are, then, the microeconomic underpinnings of scars from recessions?

In this paper, we examine one channel by which crises, financial crises especially, may generate firm dynamics that lead to aggregate TFP losses. Using a simple extension of Manova's (2013) model of firm dynamics in the presence of heterogeneous credit constraints, we argue that, when working capital is necessary to cover fixed costs of production, credit constrained businesses may have to exit the market even if productive enough to have positive expected net present value. The exit of relatively high productivity businesses leads to aggregate TFP losses. This distortion is magnified during crises, when working capital is harder to obtain.

We study the empirical merits of this hypothesis by assessing whether financially constrained manufacturing establishments in Colombia are more likely to exit than equally productive but unconstrained establishments, especially during a stark recession. We also use our estimates of exit probabilities to quantify possible TFP losses associated to a recession similar to the one lived in Colombia at the end of the nineties, the largest since the 1930's.

The Colombian case lends itself naturally to this investigation, both because of the occurrence of the end-of-century crisis, and because there are rich micro data on all non-micro manufacturing establishments. Using these data, the researcher can document survival, productivity and detailed proxies for access to credit at the micro level. Interestingly, measures of firm economic activity in our data allow us to control for productivity differences in constructing plant-specific measures of credit constraints, easing one of the main concerns that usually arise when attempting to measure firm access to credit. Further, we exploit variability across sectors in the dependence on external financing when estimating the effects of credit constraints.

we find that credit-constrained plants in sectors with high dependence on external finance are more likely to exit during a recession than their counterparts, for given productivity levels. The difference is much smaller, and statistically insignificant, during good times. In a sample with an average exit rate of 3% and where 13% of the observations are classified as constrained, the estimated gap in exit probabilities between constrained and unconstrained plants is about 5 percentage points during recessions but less than 1 percentage points during good times, for a plant in the 10th percentile of the TFP distribution. These results imply that the exit probability of an unconstrained plant with TFP at the 10th percentile is matched by that of a constrained establishment with much higher TFP, especially in bad times: the 79th percentile during downturns, and the 21st percentile in good times.

These findings indeed suggest potential scarring effects of recessions stemming from credit market imperfections. To get a quantitative sense of this scarring effects, we use our exit estimations to simulate TFP distributions for surviving plants after a recession, comparing scenarios with and without credit constrained plants. We estimate that, if a random group of 1/3 of plants were subject to credit constraints, these constraints would cost an aggregate TFP loss of about 1.2 log points after a four-year recession with respect to a scenario where no plant is credit constrained. The loss is only 0.4 log points if those four years are good times. The same simulation implies that the weighted mean of TFP of the constrained plants forced out of the market by the recession is 13.6 log points higher than that of unconstrained ones. These results point at significant efficiency losses due to constraints during recessions, as productive but credit constrained plants are shed out of the market. In this sense, our results are a step toward reconciling the micro and macro evidence regarding the long-run consequences of recessions. They also add to the evidence linking credit constraints and aggregate efficiency.

The long tradition documenting long-lived scars of recessions goes back to Blanchard and Summers' (1986, 1987) studies, where the case was made that short run fluctuations in the unemployment rate led to long-run increases in the natural unemployment rate in Europe during the 1980s. The recent global financial crisis has motivated new evidence suggesting that crises might leave permanent scars. Gali (2015) claims that "the unemployment rate in the euro area appears to contain a significant nonstationary component, suggesting that some shocks have permanent effects on that variable." Ball (2014) examines potential output in the aftermath of the Great Recession in 23 OECD countries finding that its average loss, weighted by the sizes of their economies, is 8.4%. Studying a sample of over 100 recessions from industrial countries, Blanchard, Cerutti and Summers (2015) show that output never returned to previous trends in most of these cases. In Latin America and the Caribbean, deep recessions caused by demand contractions have led to large increases in trend unemployment, according to Ball, De Roux and Hofstetter (2013).

The long run losses from crises seem particularly deep in the case of financial crises. Abiad et al., (2009) and the IMF (2009) find that, on average, although output *growth* does return to the pre-crisis rate after banking crises, the output *level* remains below the pre-crises trend in the medium run. Cerra and Saxena (2008) also find that recoveries are weak when output contractions are associated with a financial crisis, leading to significantly lower growth in the aftermath of the associated recession. These findings suggest that lack of access to financing may be one of the mechanisms preventing output recovery to its prior trend.

Paradoxically, for a long time the theory of firm dynamics focused on potential long run gains–rather than losses–from recessions. Caballero and Hammour (1994) characterize the potential of recessions as times of cleansing, on the basis that recessions may push firms exhibiting outdated technologies out of the market. A related strand of the literature notes that during recessions there is a reduction of the opportunity cost of engaging in activities that will contribute to future productivity gains, thus providing another potentially positive consequence of recessions on aggregate TFP (e.g., Cooper and Haltiwanger, 1993; Aghion and Saint Paul, 1998).

The apparent contradictions between this view and the macro evidence have motivated recent work on crisis-times firm dynamics with potential negative aggregate consequences. Based on the observation that recessions disproportionally affect young businesses, Ouyang (2009) suggests that recessions force the exit of young businesses and thus prevent them from reaching their full potential. In her calibrations, this scarring effect of recessions dominates the cleansing effect. Hallward-Driemeier and Rijkers (2013) show micro evidence for Indonesia's manufacturing businesses consistent with the implication in Ouyang's model that recessions may shed out of the market businesses that are not necessarily unproductive. More generally, they report an attenuation of the link between productivity and exit during the Indonesian crisis of the end of the 20th century.

Though Ouyang does not model the reasons why young businesses are more likely shed out of the market by recessions than older ones, credit market failures affecting young businesses disproportionately may play a role. Barlevy (2003) argues that credit constraints might lead to an inefficient allocation of resources, particularly in bad times.

He proposes a model where more productive firms are more likely to face binding credit constraints, especially during recessions, because of the higher financing needs of larger operations. Credit constraints thus distort the allocation of resources against the more productive businesses.

The mechanism we propose is also related, in that credit constrained businesses may be particularly damaged by recessions, and this sensitivity introduces distortions that lead to efficiency losses. Our contribution is twofold. First, we propose an additional channel for scars from recessions: inefficient exit related to the difficulties faced by credit constrained businesses to keep up with fixed costs of production in times of short liquidity. Second, we provide an empirical assessment of the merits of this hypothesis, including a quantification of potential associated TFP losses. These two contributions help reconcile macro evidence of long run scars from recessions with theories of firm dynamics.

Heterogeneity in credit constraints across businesses plays a crucial role in the mechanism we propose. In this sense, our paper falls in the tradition that relates idiosyncratic distortions–in access to credit, in our case–to aggregate losses due to misallocation (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Eslava et al. 2013). Misallocation stemming from heterogeneous credit constraints has been modelled by Midrigan and Xu (2013). Their calibrations indicate fairly small losses from credit constraints, because productive firms generate sufficiently large cash flows to rapidly overcome binding credit constraints. The emphasis in our paper is on how these distortions interact with the business cycle. The interaction is quantitatively important: we find both distorted exit and the associated TFP loss to be much more important during recessions than in normal times.

The rest of the paper is organized as follows. Section 2 presents a simple model of firm dynamics with heterogeneous credit constraints based on Manova's (2013), to guide our empirical work. Section 3 describes the data and how we proxy for credit constraints. Sections 4 and 5 present our main results and some extensions, followed by concluding remarks in section 6.

2 A simple model of firm dynamics with heterogeneous credit constraints

Our conceptual framework is Manova's (2013) model of heterogeneous firms with credit constraints, with modifications required to shift focus from the consequences of such constraints for exporting to their consequences on overall firm activity. We also incorporate the possibility that firms are heterogeneous in their access to credit, even within sectors. This is because we are particularly interested in the potential distortions to market selection implied by differential access to credit. It is widely recognized that access to credit is, among other factors, also related to firm-specific characteristics such as firm age, firm size and corporate relationships.

Manova extends a static, partial equilibrium model of firm dynamics a-la-Melitz (2003), to add credit constraints. Because, in contrast to Manova's, our focus is not on international trade, we frame our analysis within the closed economy version of the model. This section briefly presents the model and derives its main result: that firms with more restricted access to credit and belonging to more financially vulnerable sectors, are more likely to exit the market than otherwise identical firms, especially during bad times. The result will guide our estimating equations.

The demand side of the model is standard to models a-la-Melitz (2003). Utility U aggregates sector-specific CES consumption indices C_s using a Cobb Douglas technology: $U = \prod_s C_s^{\theta_s}$, where $C_s = \left[\int_{\psi \in \Psi_s} q_s(\psi)^{\sigma} d\psi \right]^{\frac{1}{\sigma}}$. Ψ_s is the set of varieties available in sector s, $\varepsilon = \frac{1}{1-\sigma} > 1$ is the elasticity of substitution between varieties, and

θ_S is the share of sector s in total expenditure Y. Denoting sector s' price index by $P_s = \left[\int\limits_{\psi \in \Psi_s} p_s(\psi)^{1-\varepsilon} d\psi \right]^{\frac{1}{1-\varepsilon}}$, the demand for variety ψ is $q_s(\psi) = \frac{p_s(\psi)^{-\varepsilon}}{P_S^{1-\varepsilon}} \theta_s Y$.

Potential firms must pay an initial sunk entry cost f_e to learn their productivity $\phi \sim G(\phi)$, where $\phi \in [0, \infty]$. Upon observing ϕ, the firm decides whether to exit the market or go on to produce. Production uses labor l at cost normalized to 1, and requires paying a per-period fixed cost f. With these assumptions, the inverse production function is $l = q/\phi$.

Firms require credit to finance a fraction d_s of their fixed costs of production.[1] As in Manova (2013) the need for external financing varies across sectors–thus the subindex in d_s-. It is widely recognized that some sectors use technologies that require investments that are larger and take longer to mature (Rajan and Zingales, 1998) or require more working capital (Raddatz, 2006). The firm can only go on to produce if it obtains the amount of credit it needs.

To obtain credit and produce, a firm makes a take-it or leave-it offer to a bank, by which it commits to a repayment of F. There is imperfect contractibility so that the bank only obtains repayment F with a probability $\lambda < 1$. With the complementary probability $1 - \lambda$, the bank can only seize the collateral. It is assumed that a fraction t_ψ of the initial entry cost f_e is used to acquire collateral. Collateral is allowed to vary by firm (where a firm is indexed by the variety ψ it produces) to recognize heterogeneity across firms in their access to credit, even within sectors. Such heterogeneity may arise because some firms belong to conglomerates while others do not; have different credit histories than

[1] The model in Manova(2013) is isomorphic, but emphasizes the need for external financing of the fixed costs of exporting, and assumes that the firm can use internal funds to pay for the costs of operating domestically. This is reasonable in the context of Manova's original model, written to explain the link between credit constraints and international trade. But, while exporting may indeed require particularly acute needs for external financing, even purely domestic firms are known to require external funding for working capital and investments on a regular basis.

others; are older than others; etc. Both d_s and t_ψ are assumed exogenous.

With these elements at hand, we start by explaining the intuition behind the mechanism we propose. The formal derivation follows. As in Melitz-type models, profitability is increasing in productivity so that, everything else equal, firms below a certain productivity level must exit the market. But, the threshold for exit is not independent of access to credit. Because there is imperfect contractibility in financial markets ($\lambda < 1$), banks cannot perfectly appropriate all of the benefits that a profitable firm can make. A firm must therefore be more than profitable to obtain financing, with the threshold level of profits larger the larger is the need for external financing (larger d_s) and the lower is the expected repayment to the bank (lower t_ψ). Exit occurs if the firm's profits fall below the threshold beyond which financing is obtained. With heterogeneity in d_s and t_ψ, firms with lower t_ψ or in sectors with high d_s may be pushed out of the market even if more productive than firms facing higher t_ψ or lower d_s. The financial distortion that pushes some profitable firms out of the market disappears if $\lambda = 1$, when credit access is perfect. And, as long as $\lambda < 1$, it is more acute in recessions, when firms may have lower collateral (lower t_ψ) and when overall market conditions are tighter (an exogenous decrease in Y) so that to be profitable firms need higher productivity than under better aggregate conditions.

We now derive these results formally, but the reader not interested in the derivation can go from this point directly to the next section at not much loss. For that reader, we simply note that the empirical specification we present in further sections incorporates indicators of "being constrained" that capture both the sector-level dependence on external finance, d_s, and the firm-level capability of accessing credit, t_ψ.

The problem of the firm that produces variety ψ is (writing $p_s(\phi)$ and $q_s(\phi)$ simply as $p_{s\phi}$ and $q_{s\phi}$ to save on notation):

$$\underset{p,q,F}{Max}\ \pi_s(\phi) = p_{s\phi}q_{s\phi} - \left[\frac{q_{s\phi}}{\phi} + (1-d_s)\,f + \lambda F + (1-\lambda)\,t_\psi f_e\right] \tag{1}$$

subject to

$$\begin{aligned} q_{s\phi} &= \frac{p_{s\phi}{}^{-\varepsilon}}{P_S^{1-\varepsilon}}\theta_s Y && \text{(2a)} \\ F &\leq p_{s\phi}q_{s\phi} - \frac{q_{s\phi}}{\phi} - (1-d_s)\,f && \text{(2b)} \\ d_s f &\leq \lambda F + (1-\lambda)\,t_\psi f_e && \text{(2c)} \end{aligned}$$

Constraint (2b) recognizes that the firm's take-it or leave-it offer to the bank is only credible if repayment F does not exceed the benefits the firm appropriates. Constraint (2c) requires F to be sufficiently large that the bank does not make negative profits on the loan. As Manova(2013), we assume that the credit market is perfectly competitive, so that the firm makes a repayment offer just enough for constraint (2c) to hold with equality. This also implies that $\pi_s(\phi) = p_{s\phi}q_{s\phi} - \left[\frac{q_{s\phi}}{\phi} + f\right]$ and that $p_{s\phi}$ and $q_{s\phi}$ are chosen by the firm to maximize this expression, subject to constraints (2a) and (2b)). If constraint (2b) does not bind, then, as in Melitz(2003), the solution involves:[2]

$$\begin{aligned} p_{s\phi} &= \frac{1}{\phi\sigma} && \text{(3)} \\ \pi_{s\phi} &= \frac{\theta_s Y}{\varepsilon\left(\phi\sigma P_s\right)^{1-\varepsilon}} - f && \text{(4)} \end{aligned}$$

(4) implies that profits are increasing in ϕ. Everything else equal, the firm goes on to produce if ϕ is large enough to ensure both: 1) positive profits and, 2) that condition (2b)

[2] To get to (4) note that in equilibrium $p_{s\phi}q_{s\phi} = \frac{p_{s\phi}^{1-\varepsilon}}{P_s^{1-\varepsilon}}\theta_s Y$, and then replace this equation and (3) into $\pi_s(\phi)$.

is satisfied. Since $F > \lambda F + (1-\lambda)\, t_\psi f_e$, it is the latter that first holds. The threshold for production, ϕ^*, is therefore given by the level of ϕ such that (2b) holds with equality. Using also (2c) and (4), ϕ^* satisfies:

$$\frac{d_s f - (1-\lambda)\, t_\psi f_e}{\lambda} = \frac{\theta_s Y}{\varepsilon}\left(\frac{1}{\phi^* \sigma P_s}\right)^{1-\varepsilon} - (1-d_s)\, f \tag{5}$$

The following result can now be stated:

Proposition 1 *All else equal, the survival threshold, ϕ^*, is higher for a firm in a sector with greater dependence on external financing (higher d_s) and for a firm with less access to credit (lower t_ψ).*

Proof. *From (5) one can write $\phi^* = AB^{\frac{1}{\varepsilon-1}}$, where $A = \frac{1}{\sigma P_s}\left(\frac{\varepsilon}{\theta_s Y}\right)^{\frac{1}{\varepsilon-1}} > 0$ and $B = \left[f\left(1 - d_s + \frac{d_s}{\lambda}\right) - \frac{1-\lambda}{\lambda} t_\psi f_e\right] > 0$. Then:*

$\frac{\partial \phi^*}{\partial d_s} = A\left(\frac{1}{\varepsilon-1}\right) B^{\frac{1}{\varepsilon-1}-1} f\left(\frac{1}{\lambda} - 1\right) > 0$

$\frac{\partial \phi^*}{\partial t_\psi} = A\left(\frac{1}{\varepsilon-1}\right) B^{\frac{1}{\varepsilon-1}-1} f_e\left(-\frac{1-\lambda}{\lambda}\right) < 0$ ■

Following Manova (2013) we can derive an estimating equation for the probability of exiting and its relationship to credit constraints and recessions. We begin by assuming that the fixed cost of operation f is a log-normally distributed i.i.d. stochastic shock, $f = \exp(-\kappa \upsilon)$ where $\upsilon \sim N(0, \sigma_\upsilon^2)$ and κ is a known parameter.[3] Though a full dynamic extension of the model to accommodate macroeconomic cycles is beyond the reach of this paper, we bring in these cycles by simply assuming that recessions affect aggregate expenditure and the value of available collateral. Aggregate expenditure is now $Y\Delta$, with $\Delta < 1$ in a recession and $\Delta = 1$ in good times; the collateral parameter is δt_ψ, with $\delta < 1$ in a recession and $\delta = 1$ in good times.

[3] Manova (2013) makes an analogous assumption regarding the fixed cost of exporting. Eslava et al (2013) also make a similar assumption regarding fixed operation cost in the context of deriving estimating equations for the probability that firms exit the market.

We define a latent variable $X_{s\psi} = \left(\frac{\phi}{\phi^*}\right)^{\varepsilon-1}$, which is greater than one if the firm's productivity falls above the survival threshold:

$$X_{s\psi} = \phi^{\varepsilon-1} \frac{(1-\sigma)\,\theta_s \Delta Y}{f\left(1+d_s\left(\frac{1-\lambda}{\lambda}\right)\right) + f_e\left(\frac{1-\lambda}{\lambda}\right)\delta t_\psi} (\sigma P_S)^{\varepsilon-1}$$

As in Manova (2013), we assume that the terms involving d_s and t_ψ can be written as a particular function of observables, such as measures of the sector's dependence on external financing, fin_dep_s, and a measure of the firm's average access to credit, cr_acc_ψ. We write $\frac{1}{f\left(1+d_s\left(\frac{1-\lambda}{\lambda}\right)\right)+f_e\left(\frac{1-\lambda}{\lambda}\right)\delta t_\psi} = \exp\left(\alpha_0 - \kappa\upsilon + \alpha_{c\delta} fin\_dep_s * cr\_acc_\psi\right)$ where $\alpha_{c\delta}$ varies depending on whether there is a recession or not, capturing the role of δ. Log-linearization leads to:

$$x_{s\psi} = \alpha + \alpha_\phi \ln\phi + \alpha_s - \alpha_t + \alpha_{c\delta} constrained_{s\psi} - \kappa\upsilon \tag{6}$$

where $x_{s\psi} = \ln(X_{\psi s})$; ϕ is the firm's productivity; $constrained_{s\psi} = fin\_dep_s * cr\_acc_\psi$; $\alpha_s = \ln\theta_s$; $\alpha_t = \ln\Delta < 0$ in recessions and $= 0$ in good times; and $\alpha = \ln\left((1-\sigma)\,Y\,(\sigma P_s)^{\varepsilon-1}\right)$.

We are interested in the probability that a firm exits,

$\Pr(x_{s\psi} < 0) = \Pr\left(\upsilon < \frac{\alpha+\alpha_\phi\ln\phi+\alpha_s+\alpha_t+\alpha_{c\delta} constrained_{s\psi}}{\kappa}\right)$ where υ is normally distributed. We thus estimate a Probit model for the probability that a firm exits as a function of firm-fundamentals (captured here by measured productivity ϕ); sector fixed effects; a combined measure of the firm's access to credit and it's sector's dependence on external financing; and an indicator of whether there is recession, both alone and interacted with the time-invariant measures of credit constraints. The empirical approach and measurement are explained in further detail below.

3 Empirical approach

3.1 Data

We use panel data on Colombian manufacturing plants for the period 1995-2004. We use the Colombian Annual Manufacturing Survey (AMS), a panel of all manufacturing establishments in the country with 10 or more employees, and establishments with less employees but with sales above a certain threshold. Our unit of observation is, therefore, the plant (or establishment, we use the terms interchangeably) rather than the firm, a distinction that was irrelevant in the conceptual framework presented above.

The Survey is effectively a Census of all non-micro manufacturing establishments. It reports output, consumption of energy in physical units, employment, and capital accumulation, as well as sector identifiers, and an ID of the firm to which the plant belongs. We flag a plant as exiting in year t if the plant reported positive production in year t but not in years t + 1 through t+5. Results change little if we only use t+1 to define exit, rather than t+1 to t+5, because re-entries are rare in these data.

We build a measure of the capital stock through perpetual inventory methods. With this information, we construct measures of TFP as log residuals from a KLEM production function. In calculating TFP, we use factor elasticities previously estimated by Eslava et al. (2004) through an instrumental variable approach, using the same data source. Eslava et al. (2013) show that TFP measures obtained using these elasticities display high correlations with similar measures obtained using the same data and cost shares, or OLS estimates of the production function coefficients, to proxy for factor elasticities. Outputs and inputs are deflated using an aggregate PPI deflator, with the implication that we are measuring TFPR rather than TFPQ (Foster, Haltiwanger, and Syverson, 2008). There are reasons why this is desirable in our context, discussed further below.

For many of our estimations, including our baseline specification, we use additional information from the Superintendencia de Sociedades database (Supersociedades for short) to construct our measures of credit constraints. Supersociedades is the government agency in charge of overseeing corporations. The open-access database reports balance-sheet information for all medium and large firms in the country, as well as some small firms, starting in 1995.[4] The unit of observation is the firm. We use information regarding cash flows and debt from this database, merged into the EAM using firm identifiers common to the two datasets.

Because we use information coming from both databases in our baseline estimations, they are restricted to plants in the AMS that belong to firms for which there is information in the Supersociedades database. Our baseline dataset thus excludes many of the small firms in the AMS–approximately two thirds of all observations in the AMS–. In an extension, we consider an approach that allows us to use all of the sample covered by the AMS, at the cost of proxying for credit constraints using firm outcomes.

Our estimation period, 1995-2004, covers a deep recession at the end of the nineties. "Bad times" in our estimations refer to a truly deep crisis: the only period in which the country displayed negative annual growth rates since the 1930s. We use seven different criteria, from previous literature, to split our sample into good and bad years for the estimation. We define bad times as years for which at least four of the seven criteria coincide in flagging a recession. The seven criteria look at GDP, GDP growth, and the occurrence of banking crises or Sudden Stops. Details are explained in the appendix. We

[4] The criteria for including a firm in the Supersociedades database have changed over time. All firms with assets or income over a certain level (20,000 or 30,000 monthly minimum wages, depending on the period) are included, as are branches of multinationals. Up to 2006, smaller firms were included if an inspected corporation owned more the 20% of the firm. Firms that do not satisfy these criteria may also be included if the Superintendent decides so. A non-trivial number of firms is included under this ad-hoc criterion every year, but that number varies substantially over time. As a result of the changing criteria for inclusion, some firms appear intermittently, while others (the larger ones) are included every year.

end up marking the recession as occurring between 1998 and 2001, both included.

3.2 Measuring credit constraints

Firm credit access (cr_acc_ψ)

Our regressor of interest in equation (6), $constrained_{s\psi} = fin\_dep_s * cr\_acc_\psi$, interacts a proxy for the sector's financial external dependence with a proxy for barriers in the firm's access to credit. Our baseline measure for the firm's (lack of) credit access, cr_acc_ψ, builds on a large tradition that recognizes that businesses that face higher financial constraints are bound to rely more heavily on internal funding to finance investments. Hsieh and Parker (2007), for instance, flag as credit constrained firms with coefficients of correlation between net operating profits (a proxy for cash flows) and purchases of fixed capital that fall in the upper third of the distribution. This type of proxy for credit constraints has been criticized on the grounds that both current net profits and investment are likely not independent from the innovations to profitability observed by the firm: positive profitability shocks are directly reflected on profits and could also lead to investments if they signaled persistent profitability gains. The implication is that cash flows and investment could be positively correlated even with perfect access to credit.

We build a measure of credit constraints in the tradition of using the profit-investment correlation to proxy for barriers in credit access, but address the aforementioned criticism by taking advantage of the rich information available to us to control for profitability shocks. In particular, we only consider the components of firms' net profits and investment rate that are orthogonal to TFP innovations when calculating the correlation coefficient between the two at the firm level (over time).[5] We rank firms by this coefficient, and flag as

[5] More preciely, we first run separate regressions of net profits on TFP innovations and of the investment rate on TFP innovations. We then take the residuals of those two regressions and, for each firm, calculate the coefficient of correlation between the two series of residuals.

credit constrained those firms in the upper third of the distribution and as unconstrained the rest of firms. This strategy actually separates firms into more and less constrained, rather than indicating that some firms are constrained and others are not. For the sake of clarity, however, we will stick to the "constrained/unconstrained" terminology throughout the text to distinguish between these two groups. Our firm-level proxy for credit constraint is:

$$cr\_acc_i = \left\{ \begin{array}{c} 1 \text{ if } rank\,(corr_i) > 2/3 \\ 0 \text{ otherwise} \end{array} \right\}$$

where $corr_i$ is the coefficient of correlation between net profits and the residual investment (both after controlling for TFP), and $rank()$ establishes the relative position of the firm that owns plant i in the distribution.

While we study plant-level exit, we measure firm-level constraints given the different units of observation in the AMS vs. Supersociedades. All of the establishments owned by a given firm are assigned the firm's dummy. The changing language we use below is due to this contrast: while we discuss plant exit and plant performance, when mentioning credit constraints we refer to the firm, rather than the plant.

The use of an indicator variable to separate constrained from unconstrained firms, along with the fact that the indicator is constant over time for a given firm, mitigate concerns about endogeneity in our estimations. Difficulties in the access to credit can be endogenous to the performance prospects of a firm: if one of a firm's establishments is at risk of closing, this may affect the firm's access to funding in financial markets. They can also be endogenous to the state of the economy, with banks being wary of extending credit when the times are bad. However, our measure of constraints is not affected by a firm or the economy facing bad times, given that it does not vary over time. Moreover, marginal differences in exit probability across plants may imply changes in our measure of constraints only for plants that are close to the threshold we use to divide the constrained from the unconstrained. This source of variability is capturing firm fixed characteristics correlated with its access to credit–whether it belongs to a wider conglomerate with access to credit, whether it produces a variety for which there are specific available lines of credit–as well as the firm's average access to credit over the period in which we observe it.

Sector dependence on external financing (fin_dep_s)

Our baseline estimation uses, as a proxy for the sector's dependence on external financing, the median ratio of short term debt to sales in the sector, defined at the three-digit level of aggregation of the ISIC classification, revision 2. In alternative estimations we use, instead, the median inventories-to-sales ratio, or the average labor costs-to-sales ratio.[6] These ratios, suggested by Raddatz (2006), are inspired by Rajan and Zingales' insight that certain technologies are characterized by greater financial needs (e.g. longer production lines that require more credit along the way). Rajan and Zingales' approach has been widely used for sector-level cross-country estimations of the effects of credit constraints, building measures of financial dependence from data on publicly listed US companies. This is also the case in Raddatz' (2006) work. While having the advantage that financial dependence in the US is arguably exogenous to economic performance in other countries, this strategy also raises concerns about how relevant are the financial needs faced by publicly listed firms in the US to explain the degree in which (often non-listed and small) firms in other contexts require external financing.

Time-invariant domestic measures of external dependence at the sector level are arguably exogenous to the performance of individual plants over time, which is the source

[6]The median for each sector is obtained across firms, from time-invariant ratios at the firm level. In turn, these time-invariant ratios correspond to the median ratio for the firm, across years.

of variation in our exit regressions (in contrast to sector-level regressions as in Rajan and Zingales' work, where the endogeneity of those measures would be clearly strong). We take advantage of this fact to use measures of sector financial needs that, because they are built from information on firms within the same context, are clearly relevant to measure external dependence for the firms in our estimation.

Our baseline measure of sector financial dependence fin_dep_s is a dummy variable indicating whether the sector's median ratio of short-term debt to sales falls in the upper half of the distribution (across sectors).[7] That is

$$fin\_dep_s = \left\{ \begin{array}{c} 1 \text{ if } rank\left(\frac{s.t.debt}{sales}\right)_s > 1/2 \\ 0 \text{ otherwise} \end{array} \right\}$$

Table A1 in the appendix lists sectors and indicates those classified as high short term debt according to this method (column 1). Analogous dummy variables are built using our other measures of dependence on external finance (columns 2-3). An additional dummy variable, which we term the "high liquidity needs" indicator, is constructed using the more strict definition that the three external dependence dummies must be 1 (column 4).

There is important, but not perfect, overlap over the three dummy variables in columns (1)-(3). Also, alike sectors naturally tend to fall close to each other: all of the machinery-producing sectors are classified as high liquidity needs, while the chemical and food sectors are not, etc. These findings are reassuring regarding how meaningful these proxies are. Compared to Rajan and Zingales' (1998) ranking of sectors, there is broad consistency in the fact that sectors producing machinery, wood products and textiles, and glass, tend to rank high (in at least some of our proxies for external dependence). But there are also important differences: apparel, textiles and leather frequently appear as high external

[7] Calculated over the weighted distribution, so that this "upper half" is an approximation: we choose the cutoff point that brings us closest to 50% of the observations falling in $fin\_dep_S = 1$.

dependence in our case but not in theirs, some of the chemicals industries rank high in their case while in ours all chemical-related sectors appear in the low external dependence portion of our table. These differences appear more related to the definitions of external financing that we implement, rather than the use of US vs Colombian data, as our ranking looks more similar to Raddatz'.

The combined credit access dummy ($fin\_dep_s * cr\_acc_i$)

Our regressor of interest is $fin\_dep_s * cr\_acc_i$, which takes a value of 1 for a plant flagged as more credit constrained if it belongs to a sector with high external dependence.

An alternative approach

In an extension of our empirical strategy, we estimate a specification that uses size as a proxy for credit constraints. Small firms have been frequently classified as credit constrained in the empirical literature, when trying to assess the effects and extents of financial market imperfections (see Schiantarelli, 1996, for an early survey). Because this extension does not use direct measures of credit constraints, it is not restricted to the set of firms that match between the AMS and the Supersociedades data. It, thus, has the attractiveness of including smaller plants.

3.3 Descriptive statistics

Table 1 presents descriptive statistics. The baseline scenario has 21,187 observations, which expand to 58,211 in the estimation where we do not rely on Supersociedades data to proxy for credit access. Close to 3% of the plants in the baseline sample exit the market over the relevant period; the low rate of failure is related to the focus on relatively larger firms, reflected also in an average plant size of 170 workers. The exit rate goes up to 6% and average employment falls to 80 in the extended sample.

The table also summarizes the different measures of credit constraints that we use:

A credit constrained plant (labeled "$CC\ plant = 1$" in our tables) is one for which $cr\_acc_i = 1$. One third of firms are classified as credit constrained, corresponding to 26.4% of year-plant observations in our baseline regression sample. In turn, 13.1% of observations are simultaneously classified as belonging to a credit constrained firm and belonging to a high short-term debt sector ($fin\_dep_s * cr\_acc_i = 1$).

3.4 Empirical model

We estimate the empirical model implied by equation (6), with a few modifications aimed at addressing concerns about biases from omitted variables or endogeneity. Indexing plants by i and years by t, the equation we effectively estimate is:

$$\Pr(exit_{it} = 1) = N\left(\begin{array}{c} \beta_s + \beta_l * L_{i,t-1} + \beta_{tfp} TFP_{it} + \beta_c constrained_i + \beta_B Bad_t \\ + \beta_{cB} constrained_i * Bad_t + e_{it} \end{array}\right) \tag{7}$$

where $exit_{it}$ takes a value of 1 if plant i exits in year t, and zero otherwise; $constrained_i$ takes the value of 1 if we classify i as belonging to a credit-constrained firm in a sector with high external dependence ($constrained_i \equiv fin\_dep_s * cr\_acc_i$, to simplify notation); Bad_t is a dummy variable that takes the value of 1 during a recession; TFP_{it} is a TFPR measure; L_{it-1} is lagged plant employment; and e_{it} is a normally-distributed error term. N is the cumulative normal probability distribution.

As usual in Melitz-type models, heterogeneity in plant fundamentals is captured in our conceptual framework by ϕ, a measure of the plant's physical efficiency in production. Our model incorporates differential access to credit as another likely source of heterogeneity across firms. But many others are not explicitly modelled, among them idiosyncratic demand shocks (Foster, Haltiwanger and Syverson, 2014), and idiosyncratic distortions on dimensions other than credit (e.g. Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008). The omission of these additional sources of variability across plants can bias our estimates of the effects of credit constraints on exit, to the extent that such additional variability is likely correlated with both variability in the probability of exiting, and the variability in access to credit. A business specialized in, for instance, outdated entertainment goods, is likely both to have difficulties accessing credit and to be shed out of the market. We deal with this concern by using a wide measurement of TFP, TFPR, that encompasses not only shocks to physical efficiency, but also shocks to demand and idiosyncratic distortions (Foster, Haltiwanger, and Syverson, 2008; Hsieh and Klenow, 2009).

We also control for plant size, measured as the number of employees, $L_{i,t-1}$. Size has been found to affect the probability that an establishment exits the market: smaller plants are more likely to exit (e.g., Gibson and Harris, 1996; Bernard and Jensen, 2007; and Baggs, 2005). It likely acts as a proxy for idiosyncratic characteristics of plants that affect their performance but that we cannot explicitly account for. We note, however, that one of those characteristics is precisely credit constraints: smaller productive units are expected to be more financially constrained than others (e.g., Gertler and Gilchrist, 1994, use firm size to proxy for capital market access). Thus, size may capture part of the effects of being constrained that we are trying to measure. To the extent that our estimate captures the effect of being constrained beyond that of size, it may be a lower bound for the overall effect of credit constraints on a firm's chances of exiting the market. In one of the extensions of our model, we focus directly on size as a proxy for credit constraints, by estimating:

$$\Pr(exit_{it} = 1) = N\left(\begin{array}{c} \beta_s + \beta_l * L_{i,t-1} + \beta_{tfp} TFP_{it} + \beta_B Bad_t \\ +\beta_{cB} L_{it-1} * Bad_t + e_{it} \end{array}\right) \tag{8}$$

and contrasting smaller vs. larger plants. In all of the other specifications, size is just a control and our estimates of β_c and β_{cB} capture the effects of credit constraints beyond that of size.

Our baseline specification uses a probit model as specified in (7). We also estimate analogous linear specifications that allow us to add plant fixed effects instead of the sector effects, to control for other fixed plant characteristics that may correlate with the presence of credit constraints. The plant fixed effect absorbs the effect of $constrained_i$ in these linear specifications, so we are unable to estimate β_c in these cases, but can still estimate β_{cB}, our main coefficient of interest.

4 Baseline Results

4.1 Estimated exit models

Table 2 (column 1) and Figure 1 present our baseline results. Regression coefficients are presented in the upper panel of Table 2, and the implicit marginal effects of interest are evaluated in the lower panel of the Table, as well as Figure 1. Our baseline specification is that in column 1 of Table 2, where the "constrained" plants are those belonging to credit constrained firms in high short-term debt sectors, and a probit estimation is used. Figure 1 contrasts estimated exit probabilities for constrained/unconstrained plants in bad/good times, based on the probit estimation reported in column 1. The lower panel of Table 2 quantifies the corresponding exit premia, and evaluates their statistical significance at different points of the TFP distribution.[8]

Estimated exit probabilities are higher for constrained plants than for their unconstrained counterparts (Figure 1). The effect is large and statistically significant in recessions. For instance, during a recession an average TFP plant (TFP=1.05) faces an exit probability close to 6% if constrained, but only 2.7% if unconstrained, for a 3.3% difference (lower panel of Table 2). Though for good times there is also a positive difference between constrained and unconstrained plants, it is much smaller in size (0.4%) and not statistically significant.

Correspondingly, recessions have a strong positive effect on the probability of exiting for constrained plants, and a smaller but still significant effect for unconstrained ones. The magnitudes of the effects on exit probabilities during recessions for mean TFP plants are, respectively, 3.5 pp and 0.7 pp for constrained and unconstrained plants. The implication is a large exit "premium" for constrained plants in bad vs. good times of 2.8 pp.

All of these effects are magnified if evaluated at lower TFPs, probably the appropriate thing to do given the low exit rates of approximately 3% in our baseline sample. The exit premium for constrained plants in recessions vs. good times grows from 2.8 pp for the average TFP plant to 5.2 pp for a plant in the third percentile of TFP. We also note that, consistent with the literature, results in Table 2 indicate that smaller and less productive plants face larger chances of exiting the market (e.g., Eslava et al., 2013; Bernard and Jensen, 2007).

Qualitatively similar results are found when estimating the fixed effects model, though in this case, by construction, we are unable to estimate a base effect of being constrained during good times, absorbed by plant fixed effects. In this linear model, where the magni-

[8] For comparability between the probit and fixed effects estimation, we present the exit premium for recessions vs. good times rather than the premium for constrained vs. unconstrained businesses. Notice that the latter cannot be estimated in good times for the fixed effect model, as it gets absorbed by the fixed effect.

tude of effects is independent of the level of TFP, the effect of credit constraints over the cycle is similar in magnitude to that evaluated for the probit model at the tenth percentile of TFP.

We also explore how these effects change when we ignore the variation arising from sector-level financial dependence. In particular, we re-estimate the model redefining $constrained_i = cr\_acc_i$, rather than $constrained_i = fin\_dep_s * cr\_acc_i$. Results are presented in the rightmost panel of Table 2, and in the upper left panel of Figure 2. They are qualitatively similar to those obtained for our baseline specification, though the magnitude of the exit premiums of being constrained during bad times is reduced to half that of our baseline results.

4.2 TFP implications

These results point at sizeable effects of credit constraints on plant dynamics especially during bad times. They suggest an aggregate inefficiency coming from financial constraints: plants belonging to constrained firms may have to exit the market even when they are sufficiently productive to have survived in the absence of constraints. Put differently: some establishments exit while being more productive than others that survive, solely because they face financial constraints. And, this is more likely to be the case during recessions. To illustrate these potentially long lasting effects of recessions associated with the existence of credit constraints, and get an idea of their possible magnitude, we build two counterfactual analyses derived from the results presented above.

Our first counterfactual takes the predicted exit probability of an unconstrained plant with low TFP (10th percentile), and estimates what TFP level (percentile) would leave the exit probability unaltered if the firm to which the plant belongs were to move from $constrained_i = 0$ to $constrained_i = 1$. Results from this exercise are reported in panel

A of Table 3. During bad times, the TFP would have to increase to the 79th percentile in order to leave the exit probability unchanged when moving to the constrained status. In other words, during bad times, moving from unconstrained to constrained status has a quantitative effect in exit equivalent to reducing productivity from the 79th percentile to the 10th. The same counterfactual for good times implies a move in TFP from the 21st to the 10th percentile.

To take a closer look at the implications of constraints on TFP we use the baseline regression to simulate how the TFP distribution of plants could have evolved from 1997 to 2002 (i.e. over the recession period) due to exit, in alternative scenarios without and with credit constraints. The former is a scenario where we assume that no plant is credit constrained (imposing $constrained_i = 0$ for all plants). The latter is one where a random third of plants are assigned $constrained_i = 1$. Our simulation is first conducted under the assumption that times were bad ($Bad_t = 1$), and then assuming good times ($Bad_t = 0$), to finally compare the two scenarios.

The simulation predicts exit/survival recursively over the recession period, from 1997 to 2002, for the different plants that were present in our sample over that period. It starts with the actual distribution of plants, and their observed employment (L_{it-1}) and TFP_{it} in 1997, the year prior to the recession. To simulate exit/survival patterns over the period for each plant we follow the steps described below:

1. We predict the probability of exiting for each plant present in 1997, $\Pr(exit_{it} = 1 | L_{i,t-1}, tfp_{i,t}, constrained_i, Bad_t, t = 1997)$, based on our baseline results (column 1 of Table 2). We do this imposing either $constrained_i = 0$ for all observations or $constrained_i = 1$ for a random third, and either $Bad_t = 1$ for all observations or $Bad_t = 0$ for all observations. All plants are treated as if they belonged to the same sector, so sector effects do not affect our prediction.

2. For each plant in that sample, we then predict whether the plant exited or survived from 1997 to 1998. To do this, we first rank plants according to their predicted exit probability, $\Pr(exit_{it} = 1|L_{i,t-1}, tfp_{i,t}, constrained_i, Bad_t, t = 1997)$. The plants with largest predicted exit probabilities are assumed to exit, in a number chosen to match the sample's exit rate for the respective times (good or bad, depending on the scenario being simulated).

3. Plants predicted to survive in the previous step are included in the initial distribution of plants for 1998, together with the plants that actually entered our data in 1998. Survivors from 1997 are assigned a 1998 level of TFP based on a projection of an estimated AR1 process for TFP, and their actual realization of TFP in 1997. New plants are assigned their actual 1998 entering level of TFP. Initial L is kept constant throughout the simulation, at the entry level of L (1997 or 1998, depending on whether the plant is a 1997 survivor or a 1998 entry).

4. We proceed to predict the probability of exiting for each plant in this 1998 sample, $\Pr(exit_{it} = 1|L_{i,t-1}, tfp_{i,t}, constrained_i, Bad_t, t = 1998)$, and continue iterating over the previous three steps until $t = 2002$. In the end, we are left with a simulated sample of plants and their respective TFPs for each of the years of the simulation, for each simulation scenario ($constrained_i = 1$ or 0; $Bad_t = 1$ or 0).

Measures of the resulting TFP distributions are reported in Figure 3, and in Panel B of Table 3. Figure 3 shows the simulated TFP distribution of plants eliminated by recessions (those that survive in good times but not in bad times), alternatively under the scenario with no credit constraints and the one with credit constraints. This is the distribution of firms that are shed out of the market solely due to the recession. This "lost" TFP distribution is shifted to the right in the presence of credit constraints. The difference is sizable (Table 3): on a weighted average basis, plants forced out of the market by recessions are 13.6 log points more productive in presence of credit constraints than in their absence.

We also calculate aggregate TFP by the end of the period (i.e. taking into account only plants that survive up to 2002, with their 2002 TFP draws). The figure for the recession is 1.2 log points lower in the presence of credit constraints than in their absence, a sizeable loss. If the period had been one of good times, instead, the loss would have been a more modest 0.4 log points.

5 Robustness analysis

This section tests the robustness of our results by extending them in several directions. We start with an alternative exit model that looks at the effect of size on exit over the cycle, rather than using an explicit measure of credit constraints. We also report results using alternative measures of sector dependence on external finance. Finally, we estimate models where the effects of credit constraints over the cycle are allowed to vary with the plant's TFP even in the FE estimation. This is motivated by the fact that low productivity firms may be penalized by the market with poorer access to credit. If this were the case, the efficiency costs of the distortions caused by credit constraints would be lower.

The first two columns of Table 4 show results for the alternative model where the size of the firm is interpreted as proxying for its degree of access to credit markets (equation 8). Our results are qualitatively similar to those obtained in the baseline specification. Smaller (i.e. more credit constrained) firms have a larger exit probability. Moreover, the effect is magnified by bad times in a statistically significant way. To compare the magnitudes of the estimated effects to those obtained in the baseline estimation, one needs assumptions regarding the level of L_{it-1} that corresponds to a constrained (unconstrained) plant. The calculations in the lower panel of Table 4 assume that an average constrained plant has 20 employees, while an unconstrained one has 50. With these assumptions, the magnitude of estimated effects is much smaller than our baseline estimates, but still significant in statistical and economic terms. Estimated effects are also flatter over the TFP distribution with this alternative approach.

The remaining columns in Table 4 report our baseline regressions but now using alternative definitions of the sectors' dependence on external finance. Results are remarkably close to those in Table 2. Constrained firms have a higher exit probability, more so during bad times, under all definitions of sector dependence on external financing. In the regressions with fixed effects, the constrained exit premium during bad times hovers around 4%. Similar numbers are obtained for the probit models evaluated at the third percentile of TFP. The results of our simulation of changes in TFP distributions due to exit induced by credit constraints in recessions are also similar with these alternative measures of sectoral financial dependence (Figure 4).

Finally, we check the robustness of our findings to including interactions between our variables of interest and TFP (Table 5). The results are qualitatively similar in these fully interacted models, with magnitudes even larger than those estimated in our baseline case, especially for lower levels of TFP. The counterfactual analysis of the upper panel of Table 3 is also quantitatively robust to the use of this alternative interacted model: the TFP level that makes a constrained plant as likely to exit as an unconstrained plant with TFP in the 10th percentile is 21% in good times and 73% in bad times, compared to 21% and 79% using the baseline model .

6 Conclusions

Financial frictions play a crucial role in explaining how firms adjust to short term macroeconomic fluctuations. We find, for the case of Colombia, that potential scarring effects of recessions are likely boosted by credit market imperfections. While we find throughout a family of empirical specifications that low productivity plants are the most likely to exit the market, there are further differences across plant exit probabilities explained by the degree of access to financial markets. Particularly in bad times, plants in constrained firms exhibit a larger exit probability than plants with similar market fundamentals but belonging to unconstrained firms. Our results point at aggregate TFP losses from recessions. In particular, during a recession, credit constrained units may be forced to leave the market despite being more productive than some of their surviving but unconstrained counterparts. We find that plants forced out of the market by recessions are close to 13 log points more productive, and aggregate productivity after a five-year recession is 1.2 log points lower, in presence of credit constraints than in their absence.

The evidence we have presented helps reconcile macro results suggesting long-run consequences of short-run fluctuations with theoretical predictions from the firm dynamics literature emphasizing potential cleansing effects of recessions. In particular, our findings point at a channel where the scarring effects of recessions operate through financial constraints that might leave marks on aggregate TFP levels difficult to overturn in the short run through entry of new productive plants.

While our paper does not explore the determinants of credit constraints, it is likely that they are associated with firm size, age, geographical location, and previous ties with the financial system. Previous studies have in fact pointed at the association between these firm characteristics and lack of access to credit. Some of these associations suggest additional dynamic costs to the economy from the exit of financially credit constrained establishments. In particular, at an aggregate level, the persistence of low levels of financial penetration may be partly explained by inefficiently high exit of young and small establishments. Exit prevents those establishments from reaching a scale that would allow them wider access to credit. It also truncates their chances of ever establishing a relationship with financial institutions that may prove self perpetuating, and destroys the value implicit in the still fragile relationships some of the exiting plants may have created with the financial system.

Several policy implications emerge. First, countercyclical policies become more relevant in a world where long-run outcomes are dependent on the cycle. Second, policies and regulations aimed at deepening credit markets might help mitigate the long-run consequences of bad times. Alleviating credit tightening after international supply-side financial crises, and more generally trying to ensure financial stability, also stand as important in light of these findings. Importantly, these results point at the key role of facilitating access to credit for working capital, rather than only for long-term investment, especially during economic downturns.

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Appendix

Good vs. bad times:

We consider seven criteria to separate good from bad times. We list those criteria below. We end up defining bad times as years that satisfy at least three of the seven criteria listed below.

a. Bad times are years with negative annual per capita GDP growth.

b. Bad times are years with negative annual GDP growth.

c. Trough to Peak strategy (e.g. Braun and Larrain): Calculate the cyclical component of GDP with an HP filter. For this, we used GDP data going back at least to 1960 and up to 2008. Calculate de standard deviation of the cyclical component. Indentify troughs defined as cases when the cyclical component is more than one standard deviation below zero. Then go back in time until we find a peak, defined as a year when the cyclical component is larger than the two adjacent observations. The recession years (bad times) start one year after the peak and end at the trough.

d. Bad times are years with at least two consecutive quarters with negative GDP growth.

e. Bad times are Sudden Stop years. We use the definition by Calvo, Izquierdo and Mejia (2008). Systemic Sudden Stops are phases defined by the following conditions: (i) There is at least one observation where the year-on-year fall in capital flows lies at least two standard deviations below its sample mean; (ii) A Sudden Stop starts the first time the annual change in capital flows falls one standard deviation below the mean (iii) The Sudden Stop phase ends once the annual change in capital flows exceeds one standard deviation below its sample mean.

f. Bad times are years with banking crises. The starting dates of baking crises are years when at least one of the following conditions holds: there are extensive depositor runs; the government takes emergency measures to protect the banking system, such as bank holidays or nationalization; the fiscal cost of the bank rescue is at least 2 percent of GDP; non-performing loans reach at least 10 percent of bank assets. Following these definitions Dell'Ariccia Detragiache and Rajan, (2008) find a banking crisis inception date in 1999 for Colombia. They propose a banking crisis dummy taking the value of 1 for the crisis inception year and the two following years, under the hypothesis that the real effects of the crisis take some time to disappear.

g. Bad times are years where the cyclical component of GDP is one standard deviation below zero. The cyclical component is calculated as in c.

Table A1

Three-digit Sector Description (ISIC rev. 2)	High Short Term Debt (1)	High Inventory (2)	High Labor Costs (3)	High liquidity needs (4)
Metal Products	1	1	1	1
Electric Machinery	1	1	1	1
Transportation Equipment	1	1	1	1
Machinery	1	1	1	1
Apparel	1	1	1	1
Tobacco	1	1	0	0
Textile	1	1	0	0
Leather	1	1	0	0
Pottery	1	0	1	0
Glass	1	0	0	0
Paper and Paper Products	1	0	0	0
Iron and Steel	1	0	0	0
Plastic Products	1	0	0	0
Furniture	0	1	1	0
Wood Products	0	1	1	0
Footwear	0	1	0	0
Printing and Publishing	0	0	1	0
Beverages	0	0	0	0
Rubber Products	0	0	0	0
Industrial Chemicals	0	0	0	0
Nonferrous Metal	0	0	0	0
Other Chemicals	0	0	0	0
Food Products	0	0	0	0
Other Nonmetalic Products	0	0	0	0
Petroleum Refineries and Derivates	0	0	0	0
Other Derivates from Petroleum and Coal	0	0	0	0

Table 1. Descriptive statistics

	Variable	N	Mean	St. Dev.	P10	P90
Panel A: Baseline Sample						
Performance measures	Exit Dummy	21.187	0,028	0,166	0,000	0,000
	TFP	21.187	1,052	0,678	0,316	1,839
	Labor	21.187	169,4	256,2	20,0	393,0
Dummies for credit constraints (CC)	CC plant	21.187	0,264	0,441	0,000	1,000
	CC plant in high short term debt sector	21.187	0,131	0,338	0,000	1,000
	CC plant in high inventories sector	21.187	0,115	0,319	0,000	1,000
	CC plant in high labor costs sector	21.187	0,105	0,307	0,000	1,000
	CC plant in high liquidity needs sector	21.187	0,078	0,267	0,000	0,000
Panel B: Extended Sample						
Performance measures	Exit Dummy	58.211	0,060	0,237	0,000	0,000
	TFP	58.211	1,215	0,640	0,499	1,947
	Labor	58.211	80,5	177,9	8,0	185,0

Notes: "CC plant" = plant in the upper third of the distribution of the investment-cash flow correlation.

Table 2. Determinants of Exit Probability.

	"Constrained"= CC plant in high short term debt sector		"Constrained": CC plant	
	Probit	Fixed Effects	Probit	Fixed Effects
Labor (t-1)	-0.1565***	-0.0089***	-0.1539***	-0.0089***
	(0.026)	(0.001)	(0.026)	(0.001)
TFP	-0.3396***	-0.0656***	-0.3387***	-0.0656***
	(0.034)	(0.007)	(0.034)	(0.007)
Bad	0.1413***	0.0106***	0.1391***	0.0086***
	(0.041)	(0.002)	(0.046)	(0.002)
Bad*Constrained	0.3098***	0.0442***	0.1662**	0.0296***
	(0.097)	(0.009)	(0.077)	(0.007)
Constrained	0.0942		0.0941	
	(0.082)		(0.059)	
Observations	21,106	21,187	21,106	21,187
Plant effects		x		x
Sector Effects	x		x	

Differentials in Predicted Exit Probabilities

Mean TFP				
A: Constrained-Unconstrained (Bad)	3.3%***		1.8%***	
B: Constrained-Unconstrained (Good)	0,4%		0,4%	
C. Bad- Good Times (Constrained)	3.5%***	5.5%***	2%***	3.8%***
D. Bad- Good Times (Unconstrained)	.7%***	1.1%***	.6%***	.9%***
A-B (=C-D): Constrained Premium in bad times	**2.8%*** **	**4.4%*** **	**1.4%*** **	**3%*** **
TFP 10th percentile				
A: Constrained-Unconstrained (Bad)	4.9%***		2.8%***	
B: Constrained-Unconstrained (Good)	0,7%		0,7%	
C. Bad- Good Times (Constrained)	5.4%***		3.1%***	
D. Bad- Good Times (Unconstrained)	1.1%***		1%***	
A-B (=C-D): Constrained Premium in bad times	**4.2%*** **		**2.1%*** **	
TFP 3rd percentile				
A: Constrained-Unconstrained (Bad)	6.1%***		3.5%***	
B: Constrained-Unconstrained (Good)	0,9%		0,9%	
C. Bad- Good Times (Constrained)	6.7%***		3.9%***	
D. Bad- Good Times (Unconstrained)	1.4%***		1.3%***	
A-B (=C-D): Constrained Premium in bad times	**5.2%*** **		**2.6%*** **	

Notes: "CC plant" = plant in the upper third of the distribution of investment-cash flow correlation. Robust standard errors in parentheses (clustered at the plant level in the FE estimation). *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Counterfactuals ("Constrained = CC plant in high short term debt sector)

Panel A: Counterfactual TFP percentile

	Good Times	Bad Times
Exit probability of unconstrained plant with TFP in lowest 10% of distribution is equal to exit probability of constrained plant in percentile…	21%	79%

Panel B: simulated exit results

	Weighted average (weight=initial employment)		
	No plant is Constrained	Random Constraint for 1/3 of plants	Difference
The average TFP of plants that die in bad times but not in good times is…	0,836	0,972	0,136
Bad times: the average TFP of survivors by 2002 is…	0,984	0,972	-0,012
Good times: the average TFP of survivors by 2002 is…	0,982	0,978	-0,004

Notes: both panels use baseline estimation (first column of Table 2) to project exit probabilities.

Table 4. Determinants of Exit Probability: Alternative Measures of Credit Constraints

	"Constrained" = Lagged labor		"Constrained"= CC plant in high inventories sector		"Constrained"= CC plant in high labor costs sector		"Constrained"= CC plant in high liquidity needs sector	
	Probit	Fixed Effects	Probit	Fixed Effects	Probit	Fixed Effects	Probit	Fixed Effects
Labor (t-1)	-0.1938***	-0.0113***	-0.1602***	-0.0088***	-0.1621***	-0.0088***	-0.1635***	-0.0088***
	(0.025)	(0.002)	(0.026)	(0.001)	(0.026)	(0.001)	(0.026)	(0.001)
TFP	-0.2608***	-0.0766***	-0.3415***	-0.0653***	-0.3435***	-0.0653***	-0.3435***	-0.0653***
	(0.016)	(0.005)	(0.034)	(0.007)	(0.034)	(0.007)	(0.034)	(0.007)
Bad	0.0796***	0.0401***	0.1502***	0.0112***	0.1613***	0.0122***	0.1653***	0.0128***
	(0.029)	(0.002)	(0.040)	(0.002)	(0.040)	(0.002)	(0.039)	(0.002)
Bad*Constrained			0.2767***	0.0448***	0.2367**	0.0388***	0.2852**	0.0449***
			(0.100)	(0.010)	(0.104)	(0.010)	(0.120)	(0.012)
Bad*Labor(t-1)	-0.1385**	-0.0067***						
	(0.058)	(0.001)						
Constrained			0.0531		0.0949		0.0407	
			(0.084)		(0.088)		(0.102)	
Observations	58,211	58,211	21,106	21,187	21,106	21,187	21,106	21,187
Mean Exit probablilty								
Plant effects		x		x		x		x
Sector Effects	x		x		x		x	
Differentials in Predicted Exit Probabilities								
Mean TFP								
A: Constrained-Unconstrained (Bad)	1.3%***		2.6%***		2.6%***		2.6%***	
B: Constrained-Unconstrained (Good)	.7%***		0,2%		0,4%		0,2%	
C. Bad- Good Times (Constrained)	.7%**	3.9%***	3.1%***	5.6%***	3%***	5.1%***	3.2%***	5.8%***
D. Bad- Good Times (Unconstrained)	.1%	3.7%***	.7%***	1.1%***	.8%***	1.2%***	.8%***	1.3%***
A-B (=C-D): Constrained Premium in bad times	**.6%****	**.2%*****	**2.3%*****	**4.5%*****	**2.2%*****	**3.9%*****	**2.4%*****	**4.5%*****
TFP 10th percentile								
A: Constrained-Unconstrained (Bad)	1.6%***		3.9%***		4%***		4%***	
B: Constrained-Unconstrained (Good)	.9%***		0,4%		0,7%		0,3%	
C. Bad- Good Times (Constrained)	.9%**		4.7%***		4.5%***		5%***	
D. Bad- Good Times (Unconstrained)	.2%		1.2%***		1.3%***		1.3%***	
A-B (=C-D): Constrained Premium in bad times	**.7%****		**3.5%*****		**3.3%*****		**3.7%*****	
TFP 3rd percentile								
A: Constrained-Unconstrained (Bad)	1.9%***		4.9%***		4.9%***		4.9%***	
B: Constrained-Unconstrained (Good)	1.1%***		0,5%		0,9%		0,4%	
C. Bad- Good Times (Constrained)	1%**		5.9%***		5.7%***		6.2%***	
D. Bad- Good Times (Unconstrained)	.2%		1.5%***		1.6%***		1.7%***	
A-B (=C-D): Constrained Premium in bad times	**.8%****		**4.4%*****		**4%*****		**4.5%*****	

Notes: "CC plant" = plant in the upper third of the distribution of investment-cash flow correlation. Robust standard errors in parentheses (clustered at the plant level for FE estimations).
*** p<0.01, ** p<0.05, * p<0.1.

Table 5. Determinants of Exit Probability: fully interacted models

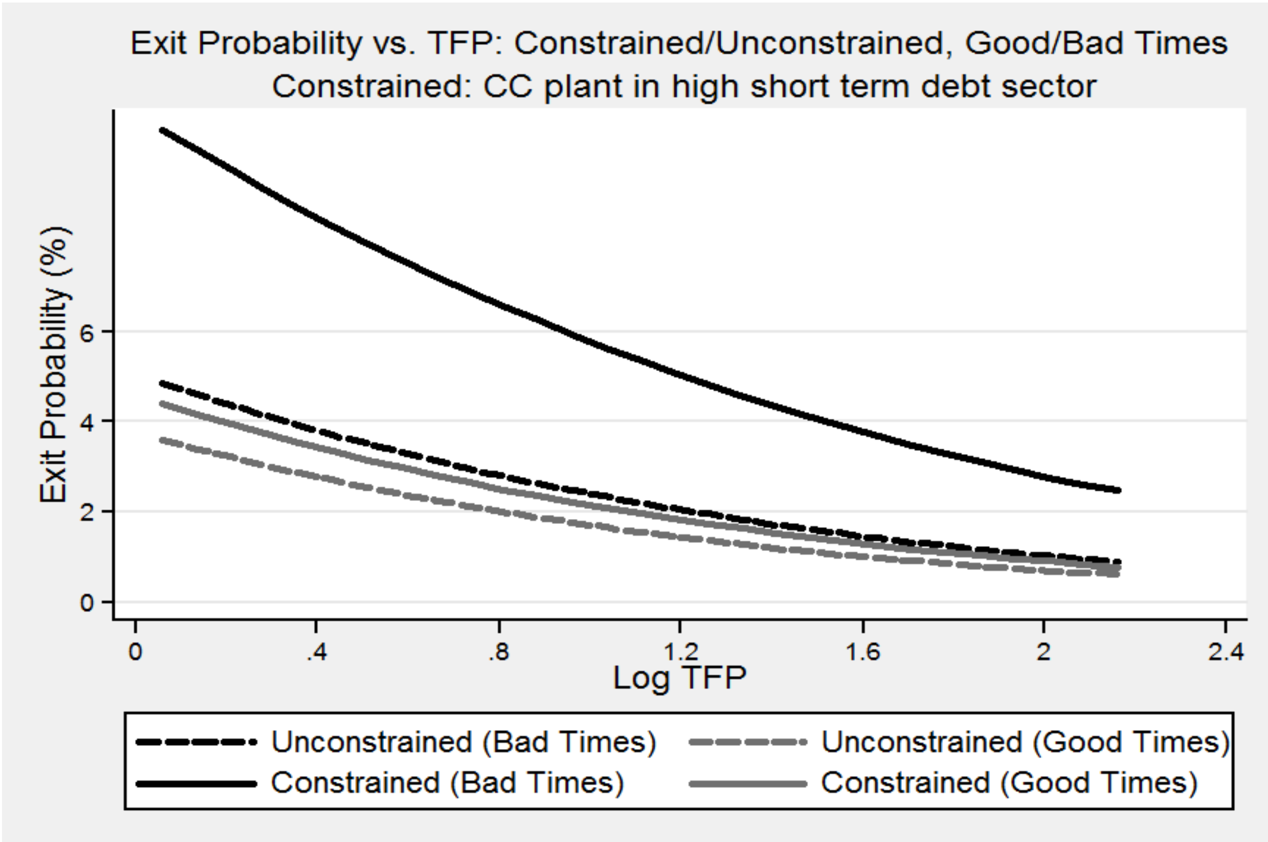
	"Constrained": CC plant		"Constrained": CC plant in high short term debt sector		"Constrained" = Lagged Labor	
	Probit	Fixed Effects	Probit	Fixed Effects	Probit	Fixed Effects
Labor (t-1)	-0.0088***	-0.1535***	-0.0087***	-0.1583***	-0.0122***	-0.1276***
	(0.001)	(0.026)	(0.001)	(0.026)	(0.002)	(0.022)
TFP	-0.0628***	-0.3457***	-0.0589***	-0.3383***	-0.0730***	-0.1951***
	(0.007)	(0.064)	(0.007)	(0.048)	(0.005)	(0.022)
Bad	0.0107*	0.1143	0.0204***	0.1798**	0.0546***	0.1217**
	(0.006)	(0.095)	(0.006)	(0.075)	(0.006)	(0.053)
Bad*Constrained	0.0601***	0.3058**	0.0702**	0.4384**		
	(0.015)	(0.136)	(0.028)	(0.207)		
Tfp*Constrained	0.0082	0.0694	-0.0121	0.1339		
	(0.012)	(0.088)	(0.016)	(0.150)		
Tfp*Bad	-0.0018	0.0267	-0.0071	-0.0158	-0.0107***	-0.0355
	(0.005)	(0.090)	(0.005)	(0.071)	(0.004)	(0.034)
Tfp*Bad*Constrained	-0.0300**	-0.1583	-0.0276	-0.1689		
	(0.012)	(0.124)	(0.023)	(0.177)		
Constrained		0.0296		-0.0872		
		(0.105)		(0.183)		
Bad*Labor(t-1)					-0.0066***	-0.1701***
					(0.001)	(0.056)
TFP*Labor(t-1)					0.0029	-0.1185***
					(0.002)	(0.024)
TFP*Labor(t-1)*Bad					-0.0021*	0.0186
					(0.001)	(0.033)
Observations	21,187	21,106	21,187	21,106	58,211	58,211
Mean Exit probablilty						
Plant effects	YES		YES		YES	
Sector Effects		YES		YES		YES

Differentials in Predicted Exit Probabilities

Mean TFP						
A: Constrained-Unconstrained (Bad)	1.6%***		3%***		1.6%***	
B: Constrained-Unconstrained (Good)	0,5%		0,5%		1%***	
C. Bad- Good Times (Constrained)	1.8%***	3.7%***	3.2%***	5%***	.7%**	4%***
D. Bad- Good Times (Unconstrained)	.7%***	.9%***	.7%***	1.1%***	.1%	3.7%***
A-B (=C-D): Constrained Premium in bad times	**1.2%****	**2.9%*****	**2.5%*****	**3.9%*****	**.6%****	**.3%*****
TFP 10th percentile						
A: Constrained-Unconstrained (Bad)	3.3%***		5.5%***		1.7%***	
B: Constrained-Unconstrained (Good)	0,4%		0,6%		.9%***	
C. Bad- Good Times (Constrained)	3.9%***	6.1%***	6%***	7.8%***	1.2%**	4.8%***
D. Bad- Good Times (Unconstrained)	.9%*	1%***	1.1%**	1.4%***	.4%	4.5%***
A-B (=C-D): Constrained Premium in bad times	**3%*****	**5.1%*****	**4.9%*****	**6.4%*****	**.9%*****	**.2%*****
TFP 3rd percentile						
A: Constrained-Unconstrained (Bad)	4.8%***		7.6%***		1.7%***	
B: Constrained-Unconstrained (Good)	0,2%		0,6%		.7%***	
C. Bad- Good Times (Constrained)	5.6%***	7.4%***	8.3%***	9.5%***	1.7%*	5.3%***
D. Bad- Good Times (Unconstrained)	1.1%	1.1%**	1,4%	1.6%***	.6%	5.1%***
A-B (=C-D): Constrained Premium in bad times	**4.6%*****	**6.4%*****	**6.9%*****	**7.9%*****	**1%*****	**.2%*****

Notes:"CC plant" = plant in the upper third of the distribution of investment-cash flow correlation. Panel B, columns 1 and 2: "constrained"= 20 employees, "unconstrained"=50 employess. Robust standard errors in parentheses (clustered at the plant level for FE estimations). *** p<0.01, ** p<0.05, * p<0.1.

Figure 1



Exit Probability vs. TFP: Constrained/Unconstrained, Good/Bad Times
Constrained: CC plant in high short term debt sector
Exit Probability (%)
0
2
4
6
0
.4
.8
1.2
1.6
2
2.4
Log TFP
Unconstrained (Bad Times)
Unconstrained (Good Times)
Constrained (Bad Times)
Constrained (Good Times)

Figure 2

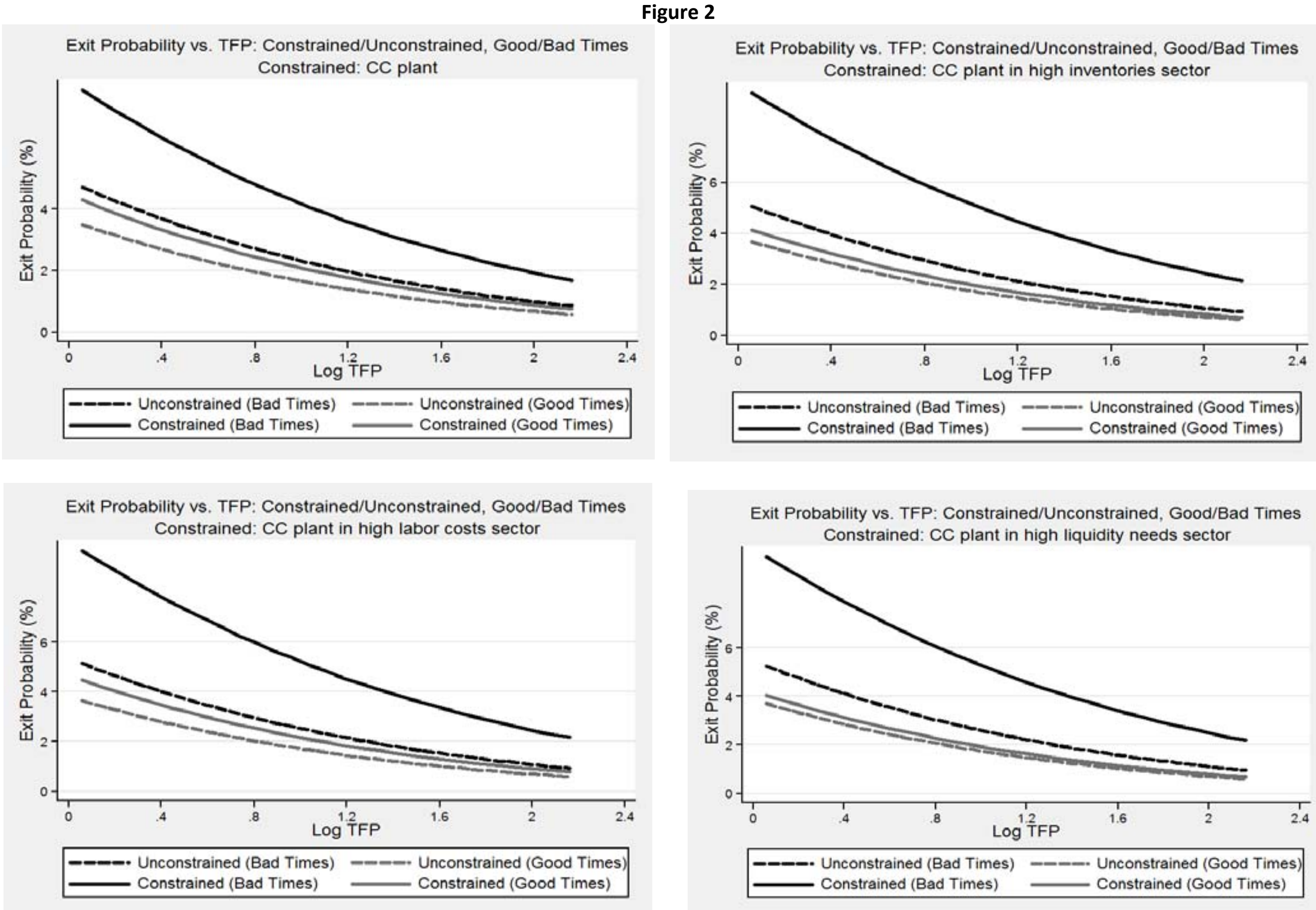

Exit Probability vs. TFP: Constrained/Unconstrained, Good/Bad Times
Constrained: CC plant
Exit Probability (%)
0
2
4
0
.4
.8
1.2
1.6
2
2.4
Log TFP
Unconstrained (Bad Times)
Unconstrained (Good Times)
Constrained (Bad Times)
Constrained (Good Times)
Exit Probability vs. TFP: Constrained/Unconstrained, Good/Bad Times
Constrained: CC plant in high inventories sector
Exit Probability (%)
0
2
4
6
0
.4
.8
1.2
1.6
2
2.4
Log TFP
Unconstrained (Bad Times)
Unconstrained (Good Times)
Constrained (Bad Times)
Constrained (Good Times)
Exit Probability vs. TFP: Constrained/Unconstrained, Good/Bad Times
Constrained: CC plant in high labor costs sector
Exit Probability (%)
0
2
4
6
0
.4
.8
1.2
1.6
2
2.4
Log TFP
Unconstrained (Bad Times)
Unconstrained (Good Times)
Constrained (Bad Times)
Constrained (Good Times)
Exit Probability vs. TFP: Constrained/Unconstrained, Good/Bad Times
Constrained: CC plant in high liquidity needs sector
Exit Probability (%)
0
2
4
6
0
.4
.8
1.2
1.6
2
2.4
Log TFP
Unconstrained (Bad Times)
Unconstrained (Good Times)
Constrained (Bad Times)
Constrained (Good Times)

Figure 3

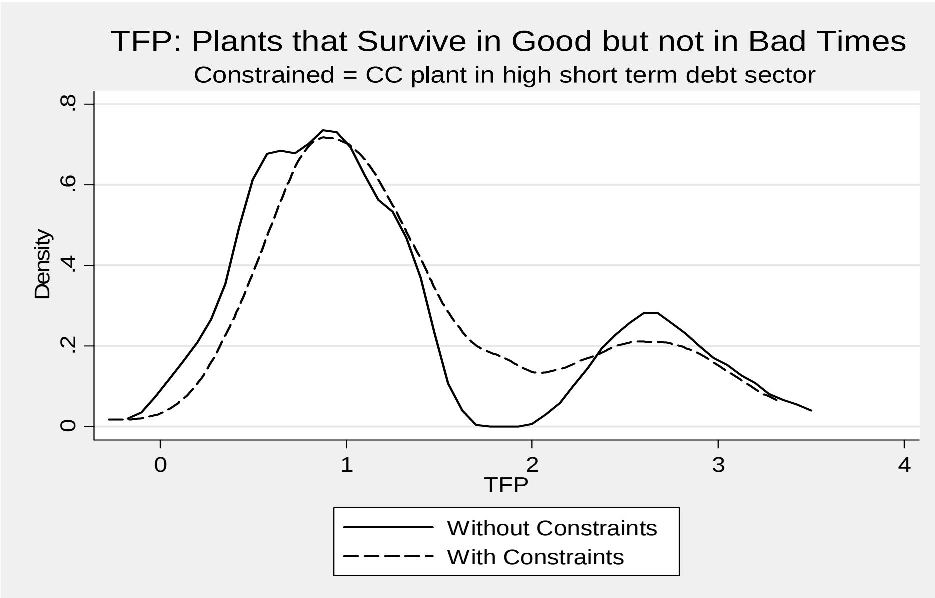
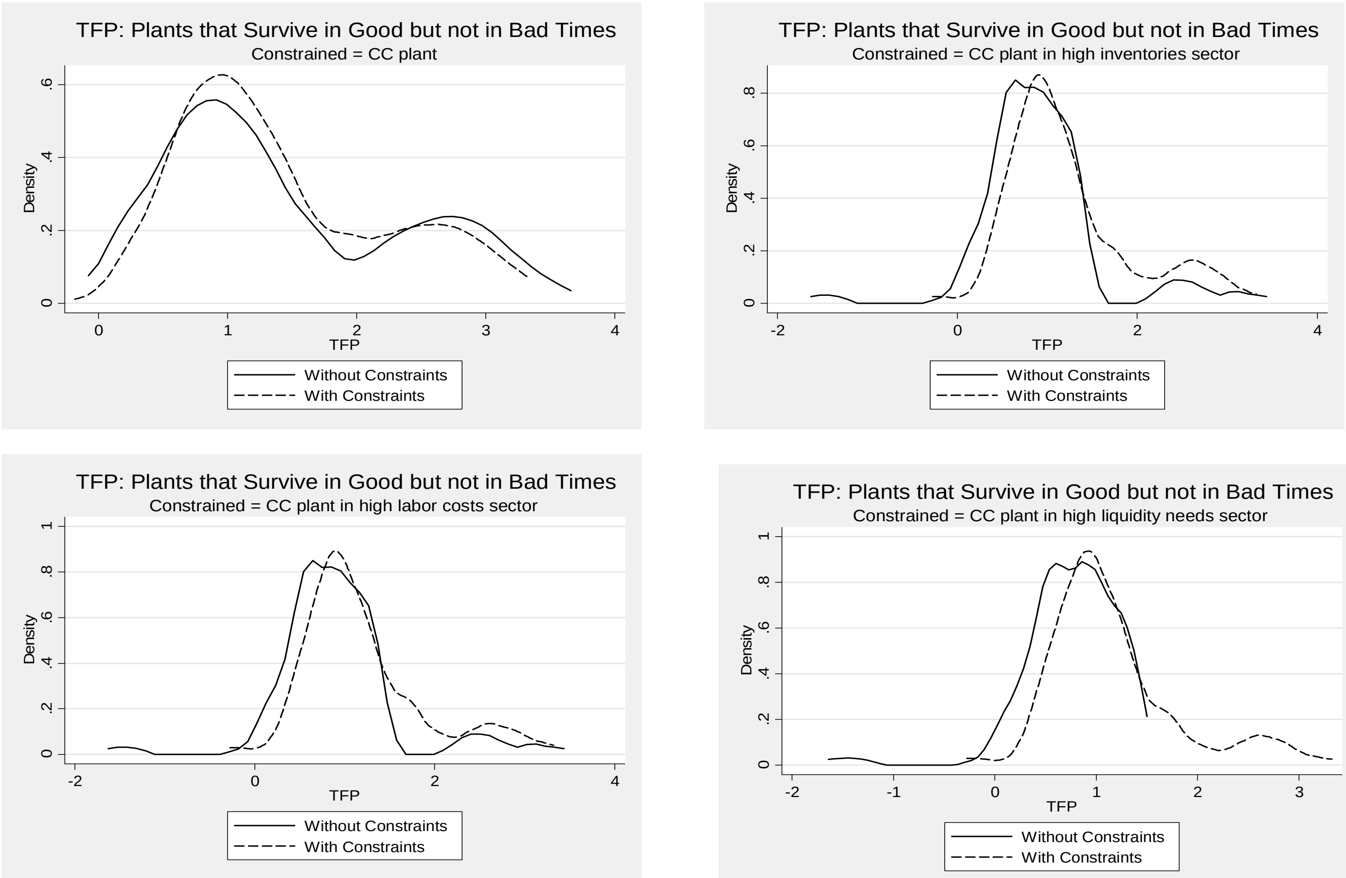

TFP: Plants that Survive in Good but not in Bad Times
Constrained = CC plant in high short term debt sector
Density
0
.2
.4
.6
.8
0
1
2
3
4
TFP
Without Constraints
With Constraints

Figure 4



TFP: Plants that Survive in Good but not in Bad Times
Constrained = CC plant
Density
TFP
Without Constraints
With Constraints
TFP: Plants that Survive in Good but not in Bad Times
Constrained = CC plant in high inventories sector
Density
TFP
Without Constraints
With Constraints
TFP: Plants that Survive in Good but not in Bad Times
Constrained = CC plant in high labor costs sector
Density
TFP
Without Constraints
With Constraints
TFP: Plants that Survive in Good but not in Bad Times
Constrained = CC plant in high liquidity needs sector
Density
TFP
Without Constraints
With Constraints