

Scarring Recessions and Credit Constraints: Evidence from Colombian Plant Dynamics

Marcela Eslava, Arturo Galindo, Marc Hofstetter and Alejandro Izquierdo*

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Abstract

Using a rich dataset of Colombian manufacturing establishments between 1995 and 2004, we illustrate potential scarring effects of recessions operating through credit constraints. In contrast with the view that recessions are times of cleansing, we find that financially constrained businesses might be forced to exit the market during recessions even if they are highly productive. For instance, during recessions, an establishment with TFP at the lowest 10th percentile but not facing credit constraints has the same exit probability as a constrained plant with TFP at the 77th percentile. The gap is much smaller during expansions. The contribution of the paper is threefold. First, it evaluates the role played by credit constraints in explaining firm dynamics throughout the business cycle, a phenomenon the literature has dealt with mostly from a theoretical standpoint. Second, it sheds light on the implied long-run consequences of exits induced by lack of credit on efficiency. Finally, it is the only study we know of providing direct evidence to judge the empirical merits of proposed micro foundations behind the long-run consequences of crises.

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

*Eslava: Associate professor, Universidad de Los Andes, email: meslava@uniandes.edu.co; Galindo: Regional Economic Advisor for the Andean Countries, IDB, email: arturog@iadb.org; Hofstetter: Associate professor, Universidad de Los Andes, email: mahofste@uniandes.edu.co; Izquierdo: Principal research economist IDB, email: alejandroi@iadb.org. The authors thank Luis Felipe Saenz and Nathalie González for very good research assistance. Eslava thanks DANE for access to data on the manufacturing industry, and advice on their use. The views in this paper are the authors' exclusively and do not necessarily represent the views of the IADB or its board of directors.

1 Introduction

The global financial crisis has brought back to town concerns over 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. These findings are at odds with a long tradition 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 TFP.

In this paper, we examine empirically one channel by which crises, financial crises especially, 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 the need for working capital is larger.

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 quantify the 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. We take advantage of rich micro data on all non-micro manufacturing establishments in the country. Detailed measures of economic activity in our data allows us to construct plant-specific measures of credit constraints that control for productivity differences.

There is a long tradition documenting long-lived scars of recessions, going back to Blanchard and Summers’ (1986, 1987) studies making the case that short run fluctuations in the unemployment rate led to long-run increases in the natural unemployment rate in Europe during the 80s. The recent global financial crisis has motivated an explosion of new evidence that crises do 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%. In Latin American and Caribbean large increases in trend unemployment have also been found to be associated with deep recessions caused by demand contractions according to Ball, De Roux and Hofstetter (2013). Financial crises have been particularly damaging. 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-crisis trend in the medium run. The findings by Cerra and Saxena (2008) indicate 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 disproportionately 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. 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 distorts the allocation of resources against the more productive businesses. Though Ouyang does not model the reasons why

young businesses are more likely shed out of the market by recessions than older ones, the mechanism she proposes may be closely related to Barlevy's since the fact that young firms more likely face credit constraints may be behind their greater sensitivity to recessions.

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 this distortion: 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 the associated TFP losses.

Heterogeneity in credit constraints across businesses plays a crucial role in this mechanism. In this sense, our paper falls in the tradition that relates idiosyncratic distortions—in the 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 credit constraints has been modelled by Midrigan and Xu (2013); their calibrated model indicates 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 while.

We find that credit-constrained plants in sectors with high external dependence for finance are more likely to exit during a recession than their counterparts, for given productivity levels. The difference is much smaller, though still statistically significant, during good times. In a sample with an average exit rate of 3%, in our baseline specification the estimated exit gap between constrained and unconstrained firms 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 establishment 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 in a five-year recession with respect to a scenario where not plant is credit constraints. The loss is only 0.4 log points if those five years are good times. The same simulation implies that weighted mean TFP of the constrained firms 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 firms 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 economic development.

The rest of the paper is organized as follows. Section 2 presents simple model of firm dynamics based on Manova's (2013) that will guide our empirical work. Section 3 describes the data and how we measure the relevant variables. 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 a few 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, even within sectors, firms are heterogeneous in their access to credit. 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 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. This result will guide our estimating equations.

The demand side of the model is standard to models a-la-Melitz(2013). Utility U aggregates sector-specific CES consumption indices C_s using a Cobb Douglas technology: $U = \prod_s C_s^{\theta_s}$, where $C_s =$

$$\left[\int_{\psi \in \Psi_s} q_s(\psi)^\sigma d\psi \right]^{\frac{1}{\sigma}} . \quad \Psi_s \text{ is the set of varieties available in sector } s, \quad \varepsilon = \frac{1}{1-\sigma} > 1 \text{ is the elasticity of substitution between varieties, and } \theta_s \text{ is the share of sector } s \text{ in total expenditure } Y. \text{ Denoting sector } s' \text{ price index by } P_s = \left[\int_{\psi \in \Psi_s} p_s(\psi)^{1-\varepsilon} d\psi \right]^{\frac{1}{1-\varepsilon}}, \text{ the demand for variety } \psi \text{ is } q_s(\psi) = \frac{p_s(\psi)^{-\varepsilon}}{P_s^{1-\varepsilon}} \theta_s Y.$$

Potential firms must pay an initial 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 w , and requires paying a per-period fixed cost f . Fixed costs are denominated in units of labor.

We further assume that 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. 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

¹The 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.

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. Such heterogeneity may arise because some firms are older than others; have different stronger histories than others; belong to conglomerates while others do not; etc. Both d_s and t_ψ are assumed exogenous.

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):

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

subject to

$$q_{s\phi} = \frac{p_{s\phi}^{-\varepsilon}}{P_S^{1-\varepsilon}} \theta_s Y \quad (2a)$$

$$F \leq p_{s\phi}q_{s\phi} - \frac{wq_{s\phi}}{\phi} - w(1 - d_s)f \quad (2b)$$

$$d_s f w \leq \lambda F + (1 - \lambda)t_\psi f_e w \quad (2c)$$

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: $F = \frac{d_s f w - (1-\lambda)t_\psi f_e w}{\lambda}$. If constraint (2b) does not bind, then, as in Melitz(2003), the solution involves:

$$p_{s\phi} = \frac{w}{\phi \sigma} \quad (3)$$

$$\pi_{s\phi} = \frac{\theta_s Y}{\varepsilon} \left(\frac{w}{\phi \sigma P_s} \right)^{1-\varepsilon} - wf \quad (4)$$

where the last term in equation (4) uses the assumption that (2c) holds with equality.

Profits are increasing in ϕ . The firm goes on to produce if ϕ is large enough to generate positive profits and if it is large enough that condition (2b) is satisfied. Since $F > \lambda \frac{F}{w} + (1 - \lambda) t_\psi f_e$, the threshold for production, ϕ^* , is given by the level of ϕ such that (2b) holds with equality. Using also (2c) and (4), ϕ^* satisfies:

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

where the RHS of equation (5) recognizes that $p_s \phi q_{s\phi} - \frac{w q_{s\phi}}{\phi} = \pi_{s\phi} + w f$ since (2c) holds.

The following result can now be stated:

Proposition 1 *The survival threshold, ϕ^* , is higher for a firm in a sector with greater need for external financing (higher d_s) and for a firm with less access to credit (lower t_ψ).*

Proof. Denoting $A = \frac{w}{\sigma P_s} \left(\frac{\theta_s Y}{\varepsilon} \right) > 0$ and $B = \left[f w \left(1 - d_s + \frac{d_s}{\lambda} \right) - \frac{1-\lambda}{\lambda} t_\psi w f_e \right]^{-\frac{1}{1-\varepsilon}-1} > 0$:

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

$$\frac{\partial \phi^*}{\partial t_\psi} = AB f w \left(-\frac{1-\lambda}{\lambda} \right) \left(-\frac{1}{1-\varepsilon} \right) < 0 \quad \blacksquare$$

Because there is imperfect contractability 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). Notice also that these distortions disappear if $\lambda = 1$.

Following Manova (2013) we can derive an estimating equation for the probability of exiting and its relationship to credit constraints. We begin by assuming that the fixed cost of operation f is an i.i.d. stochastic shock, $f = \exp(-\kappa v)$ where $v \sim N(0, \sigma_v^2)$ and κ is a known parameter.² Because we are also interested in the interaction between credit constraints and recession, we bring in macroeconomic cycles by simply assuming that recessions affect aggregate expenditure and the availability of collateral. Aggregate expenditure is now $Y\Delta$, with $\Delta < 1$ in a recession and $\Delta = 1$ in good times; the collateral

²Manova (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.

parameter is δt_ψ , with $\delta < 1$ in a recession and $\delta = 1$ in good times. A full dynamic extension of the model to accommodate macroeconomic cycles is beyond the reach of this paper.

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:

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

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 the sector's dependence on external financing, fin_dep_s , and a time-invariant measure of the firm's average access to credit, cr_acc_ψ . We write $\frac{1}{f w \left(1 + d_s \left(\frac{1-\lambda}{\lambda}\right)\right) + f_e w \left(\frac{1-\lambda}{\lambda}\right) t_\psi} = \exp(\alpha_0 - \kappa v + \alpha_{c\delta} fin_dep_s * cr_acc_\psi)$ where $\alpha_{c\delta}$ varies depending on whether there is a recession or not. Log-linearization leads to:

$$x_{s\psi} = \alpha + \alpha_\phi \ln \phi + \alpha_s - \alpha_t + \alpha_{c\delta} constrained_{s\psi} - \kappa v \quad (6)$$

where $constrained_{s\psi} = fin_dep_s * cr_acc_\psi$; $x_{s\psi} = \ln(X_{s\psi})$; $\alpha_s = \theta_s$; $\alpha_t < 0$ in recessions and $= 0$ in good times; and $\alpha = \ln \frac{(1-\sigma)Y(\sigma P_S)^{\varepsilon-1}}{w}$.

We are interested in the probability that a firm exits, $\Pr(x_{s\psi} < 0) = \Pr\left(v < \frac{\alpha + \alpha_\phi \ln \phi + \alpha_s + \alpha_t + \alpha_{c\delta} constrained_{s\psi}}{\kappa}\right)$

where v 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 its 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 thresholds. The Survey is effectively a Census of all non-micro manufacturing establishments. The AMS also reports output, consumption of energy in physical units, employment, and a measure of the capital stock constructed through perpetual inventory methods. We use this information to 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. Outputs and inputs are deflated using an aggregate PPI deflator, with the implication that we are measuring TFPR. There are reasons why this is desirable in our context, discussed further below.

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 $t+5$. We can use this five-year window without losing information because we have access to the AMS up until 2009.

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 1995.³ The unit of observation is the firm. We use information regarding cash flows and debt from this database.

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 a third 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.

³The criteria for including a firm in the 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 in the dataset, 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 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.

Our estimation period is 1995-2004, which 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 has 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 end up marking the recession as occurring between 1998 and 2001, both included.

3.2 Measuring credit constraints

Firm credit access (cr_acc_ψ)

In equation (6), our regressor of interest, $constrained_{s\psi} = fin_dep_s * cr_acc_\psi$, 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 builds on a large tradition that recognizes that a business that faces higher financial constraints is 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.⁴ 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: those innovations 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 such profitability shocks. In particular, we only consider

⁴The correlation coefficient could actually be negative in the absence of financing constraints, if businesses want to undertake investments precisely during bad times, when the opportunity costs of dedicating resources and effort to improving technology are lower (Cooper and Haltiwanger, 1993; Aghion and Saint Paul, 1998).

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 credit constrained those firms in the upper third of the distribution and as unconstrained the rest of firms. To be more precise, this strategy separates firms into more and less constrained, rather than indicating that some firms are constrained and others are not. We will, however, use the terminology "constrained/unconstrained" throughout the text to distinguish between these two groups. Our firm-level proxy for credit constraint is:

$$cr_acc_i = \left\{ \begin{array}{l} 1 \text{ if } rank(corr_i) > 2/3 \\ 0 \text{ otherwise} \end{array} \right\}$$

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

All of the establishments owned by a given firm are assigned the firm's dummy. Notice that, while we study plant-level exit, we measure firm-level constraints given the different units of observation in the AMS vs. Supersociedades. 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 measure is constant over time, mitigate concerns about endogeneity in our estimations. Credit constraints 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 either a firm or the economy facing bad times, given that it does not vary over time. Moreover, marginal differences in exit probability across

⁵More precisely, 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.

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.

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 bring 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 large firms in the US to explain the degree in which firms in very different settings require external financing.

Time-invariant domestic measures of external dependence at sector level are arguably exogenous to the performance of individual plants over time, which is the source of variation in our exit regressions. 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 ratio falls in the upper half of the distribution of the sectoral median ratio of short-term debt

⁶These medians are obtained across firms, using time-invariant ratios at the firm level. In turn, these time-invariant measures correspond to the median ratio for the firm, across years.

to sales.⁷ That is

$$fin_dep_s = \begin{cases} 1 & \text{if } rank\left(\frac{s.t.debt}{sales}\right)_s > 1/2 \\ 0 & \text{otherwise} \end{cases}$$

Table A1 in the appendix lists sectors and indicates those classified as high short term debt according to this method (column 1). Analogous dummies are built using our other measures of external dependence (columns 2-3). An additional dummy is constructed using the more strict definition that the other three financial 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 machiner-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. By comparison 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 liquidity needs). But there are also important differences: apparel, textiles and leather frequently appear as high liquidity needs 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-liquidity needs 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 much closer 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 financial 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 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

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

not restricted to the set of firms that match between the AMS and the Supersociedades data. It, thus, has the attractive 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 to 6% and average employment goes to 80 in the extended sample.

The table also summarizes the different measures of credit constraints that we use: A credit constrained plant (“*CC plant* = 1”) 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.

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:

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

where $exit_{it}$ takes a value of 1 if plant i exits in year t , and zero otherwise; $constrained_{it}$ takes the value of 1 if we classify i as a credit-constrained plant in a sector with high external dependence; Bad_t is a dummy variable that takes the value of 1 during a recession; TFP_{it} is a TFPR measure and L_{it-1} is lagged plant employment and e_{it} is a normally-distributed error term. N is the cumulative normal probability distribution. We discuss measurement in the data section.

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 Kenow, 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 variability is likely to be 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.

Size 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 some of the extensions of our model, we focus directly on size categories as proxies for credit constraints.

(7) is our main estimating equation. 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 link between TFP and exit is crucial in aggregate terms: exit improves aggregate TFP if, as predicted by theory, it is the least productive units that exit the market. We use our estimates of (7) to assess the potential for inefficient exit related to credit constraints, through counterfactual analysis and simulations.

4 Results

4.1 Estimated exit models

Table 2 and Figure 1 present our baseline results. Regression coefficients are presented in the upper panel of Table 2. Our baseline specification is that in column 1, 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 using our . The lower panel of Table 2 quantifies these exit premia, and evaluates their statistical significance at different points of the TFP distribution⁸

Estimated exit probabilities are much higher for constrained plants than for their unconstrained counterparts (Figure 1). The effect is large and statistically significant in recessions. For instance, an average TFP plant (TFP=1.05) faces an exit probability close to 6% if constrained, but only 2.5% if unconstrained. Though for good times there is also a positive difference between constrained and unconstrained plants, it is much smaller in size and not statistically significant. Conversely, recessions have a strong positive effect on the probability of exiting for constrained plants, and a smaller but still large and significant effect during for unconstrained ones. The magnitudes of the effects on exit probabilities of 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 “prima” 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 prima for

⁸For comparability between the probit and fixed effects estimation, we present the exit primum 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.

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., 2009; 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 magnitude 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 $constrained_i = cr_acc_i$. 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 primas of being constrained during bad times is reduced to about half that of our baseline results.

4.2 TFP implications

These results point at sizeable effects of credit constraints on firm dynamics especially during bad times. They suggest a possible 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 potential scarring 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 previous results.

Our first counterfactual takes the predicted exit probability of an unconstrained firm with low TFP (10th percentile), and estimates what TFP level (percentile) would leave the exit probability unaltered if the firm were to move from unconstrained to constrained. The results are reported in panel A of

Table 3. During bad times, TFP would have to increase to the 79th percentile in order to leave the exit rate 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 77th percentile to the 10th. Alternatively a constrained but highly productive firm (77th percentile in TFP) has the same chances of exiting the market than an unconstrained one with low TFP. The same counterfactual for good times is a move in TFP from the 10th to the 21st percentile. This evidence is consistent with the view of scarring effects of recessions operating through financial constraints.

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 evolved from 1997 to 2002 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 ($Bad_t = 0$).

The simulation predicts exit/survival recursively 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 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 based on our baseline results (column 1 of Table 2), under the respective assumption about constraints (either $constrained_i = 0$ for all observations, or $constrained_i = 1$ for a random third) and about the economic cycle ($Bad_t = 1$ 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. The plants with largest predicted exit probabilities are assumed to exit, in a number chose 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 conform the initial distribution of plants for 1998,

together with the plants that actually entered our data in 1998. Survivors from 1997 are assigned a new level of TFP based on a projection of an estimated AR1 process for TFP, and their actual realization of TFP for 1997. New plants are assigned their actual 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).

3. We iterate over these three steps until 2002..

Outcomes of the resulting TFP distributions are reported in Figure 3, and in Panel B of Table 3. Figure 2 shows the simulated TFP distribution of plants eliminated by recessions (those that survive in good times but not in bad times), alternatively under a scenario with no credit constraints and 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 clearly to the right in the presence of credit constraints. The difference is sizable as reported in 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. The figure is smaller but still sizeable on an unweighted basis: 9.8 log points in average.

We also calculate aggregate TFP by the end of the period (taking into account only surviving establishments) of firms predicted to have survived up until the end of the period by this simulation. 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 over the cycle rather than using an explicit measure of credit constraints. We also report results using alternative measures of sector financial dependence. Finally, we estimate models where the effects of credit constraint 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 an alternative model where the size of the firm is interpreted as proxying for its degree of access to credit markets. L_{it-1} is, consequently, also interacted with the recession dummy. Our results are qualitatively similar to those obtained in the baseline specification. Under the current interpretation, the results show that 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 what L_{it-1} 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 credit constrained definitions. Results are remarkably consistent with those in table 2. Constrained firms have a higher exit probability, more so during bad times. In the regressions with fixed effects, the constrained exit prima during bad times hovers around 4%. Very 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.

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 firms are the most likely to exit the market, there are further differences across firm exit probabilities explained by their degree of access to financial markets. Particularly in bad times, constrained firms exhibit a larger exit probability than unconstrained firms with similar market fundamentals. Our results point at aggregate TFP losses from recessions. In particular, we show that during a recession, credit constrained units may be forced to leave the market despite being much more productive than some of their surviving but unconstrained counterparts. This has might have a negative impact on aggregate long run TFP to the extent that re-entry is unlikely due to high entry costs. We show that plants forced out of the market by recessions are close to 22% more productive in presence of credit constraints than in their absence. In this sense, 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 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 permanent marks on aggregate TFP levels.

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 the 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, based on our evidence, the role of financial frictions explaining this outcome is quite relevant. Thus, policies and regulations aimed at deepening credit markets might help mitigate the long-run consequences of bad times. Moreover, reducing the

frequency of recessionary periods, such as those provoked by international supply-side financial crises that invariably force more firms into credit constraints should be beneficial in terms of increasing average productivity levels. Thus, measures pointing to financial stability are also desirable. More research is needed to enhance our understanding of the consequences of credit constraints, particularly for smaller firms for which financial information is not as readily available as it is for their larger counterparts.

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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 the standard deviation of the cyclical component. Identify 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 banking 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 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	169.379	256.190	20.000	393.000
Dummies for credit constraints (CC)	CC plant	21187	0.264	0.441	0.000	1.000
	CC plant in high short term debt sector	21187	0.131	0.338	0.000	1.000
	CC plant in high inventories sector	21187	0.115	0.319	0.000	1.000
	CC plant in high labor costs sector	21187	0.105	0.307	0.000	1.000
	CC plant in high liquidity needs sector	21187	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*** (0.026)	-0.0089*** (0.001)	-0.1539*** (0.026)	-0.0089*** (0.001)
TFP	-0.3396*** (0.034)	-0.0656*** (0.007)	-0.3387*** (0.034)	-0.0656*** (0.007)
Bad	0.1413*** (0.041)	0.0106*** (0.002)	0.1391*** (0.046)	0.0086*** (0.002)
Bad*Constrained	0.3098*** (0.097)	0.0442*** (0.009)	0.1662** (0.077)	0.0296*** (0.007)
Constrained	0.0942 (0.082)		0.0941 (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 Prima 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 Prima 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 Prima 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 of constrained plant to exit with likelihood of an unconstrained plant

	Probit model without interactions		Probit model with interactions	
	Good Times	Bad Times	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 lowest...	21%	79%	21%	73%

Panel B: simulated exit results (probit model with no interactions)

	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...	0.8356	0.9717	0.1361
Bad times: the average TFP of survivors by 2002 is...	0.9838	0.9720	-0.0118
Good times: the average TFP of survivors by 2002 is...	0.9824	0.9782	-0.0043

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*** (0.025)	-0.0113*** (0.002)	-0.1602*** (0.026)	-0.0088*** (0.001)	-0.1621*** (0.026)	-0.0088*** (0.001)	-0.1635*** (0.026)	-0.0088*** (0.001)
TFP	-0.2608*** (0.016)	-0.0766*** (0.005)	-0.3415*** (0.034)	-0.0653*** (0.007)	-0.3435*** (0.034)	-0.0653*** (0.007)	-0.3435*** (0.034)	-0.0653*** (0.007)
Bad	0.0796*** (0.029)	0.0401*** (0.002)	0.1502*** (0.040)	0.0112*** (0.002)	0.1613*** (0.040)	0.0122*** (0.002)	0.1653*** (0.039)	0.0128*** (0.002)
Bad*Constrained			0.2767*** (0.100)	0.0448*** (0.010)	0.2367** (0.104)	0.0388*** (0.010)	0.2852** (0.120)	0.0449*** (0.012)
Bad*Labor(t-1)	-0.1385** (0.058)	-0.0067*** (0.001)						
Constrained			0.0531 (0.084)		0.0949 (0.088)		0.0407 (0.102)	
Observations	58,211	58,211	21,106	21,187	21,106	21,187	21,106	21,187
Mean Exit probability								
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 Prima 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 Prima 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 Prima 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	
	Fixed Effects	Probit	Fixed Effects	Probit	Fixed Effects	Probit
Labor (t-1)	-0.0088*** (0.001)	-0.1535*** (0.026)	-0.0087*** (0.001)	-0.1583*** (0.026)	-0.0122*** (0.002)	-0.1276*** (0.022)
TFP	-0.0628*** (0.007)	-0.3457*** (0.064)	-0.0589*** (0.007)	-0.3383*** (0.048)	-0.0730*** (0.005)	-0.1951*** (0.022)
Bad	0.0107* (0.006)	0.1143 (0.095)	0.0204*** (0.006)	0.1798** (0.075)	0.0546*** (0.006)	0.1217** (0.053)
Bad*Constrained	0.0601*** (0.015)	0.3058** (0.136)	0.0702** (0.028)	0.4384** (0.207)		
Tfp*Constrained	0.0082 (0.012)	0.0694 (0.088)	-0.0121 (0.016)	0.1339 (0.150)		
Tfp*Bad	-0.0018 (0.005)	0.0267 (0.090)	-0.0071 (0.005)	-0.0158 (0.071)	-0.0107*** (0.004)	-0.0355 (0.034)
Tfp*Bad*Constrained	-0.0300** (0.012)	-0.1583 (0.124)	-0.0276 (0.023)	-0.1689 (0.177)		
Constrained		0.0296 (0.105)		-0.0872 (0.183)		
Bad*Labor(t-1)					-0.0066*** (0.001)	-0.1701*** (0.056)
TFP*Labor(t-1)					0.0029 (0.002)	-0.1185*** (0.024)
TFP*Labor(t-1)*Bad					-0.0021* (0.001)	0.0186 (0.033)
Observations	21,187	21.106	21,187	21.106	58,211	58,211
Mean Exit probability						
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 Prima 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 Prima 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 Prima 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. 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

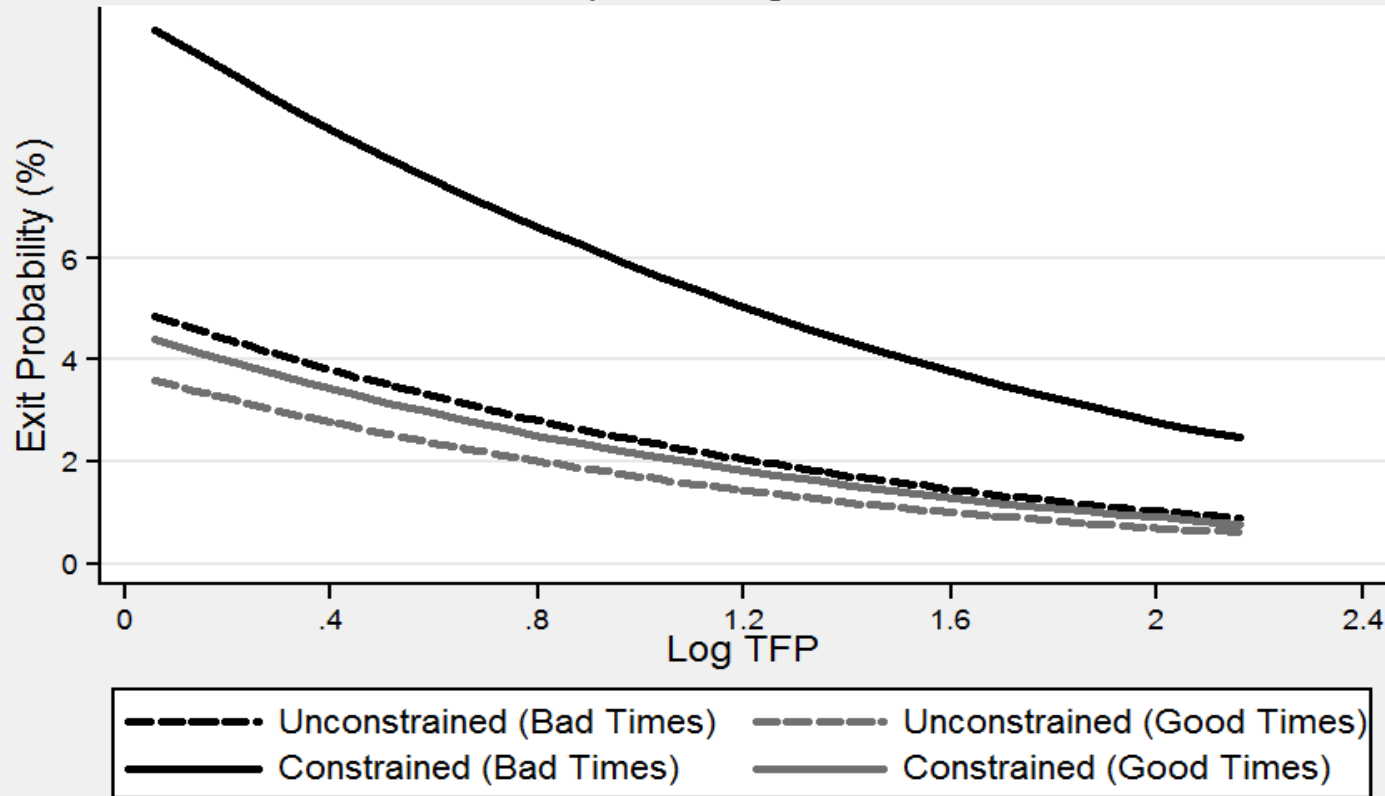


Figure 2

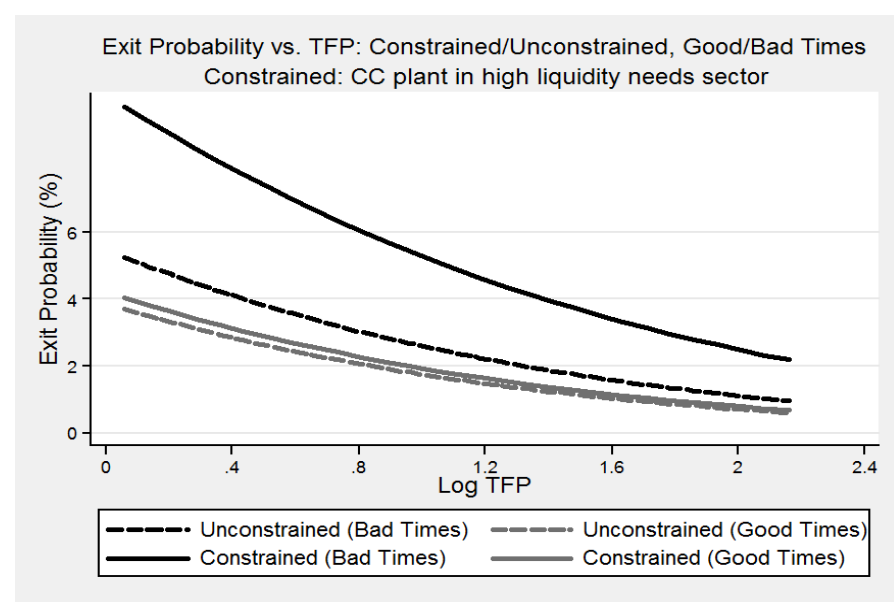
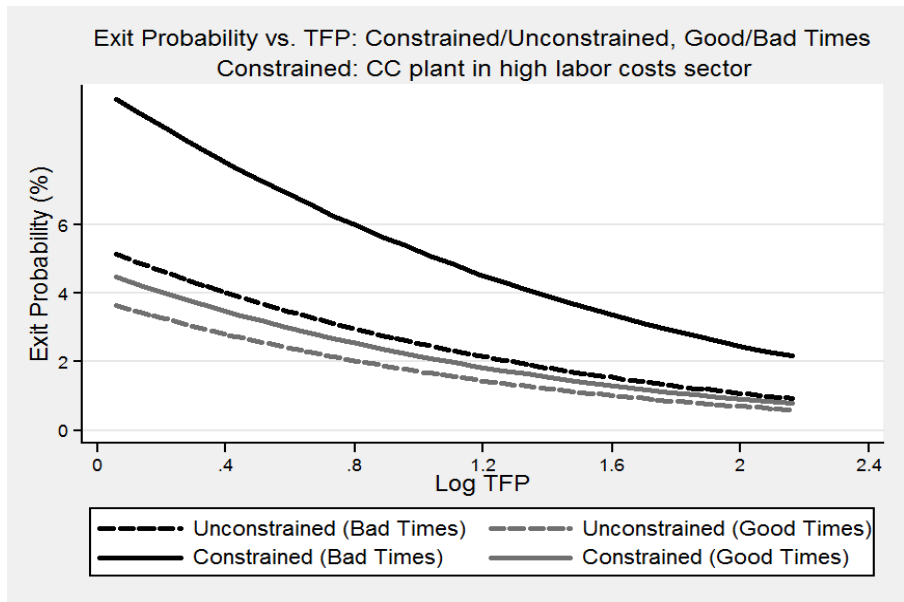
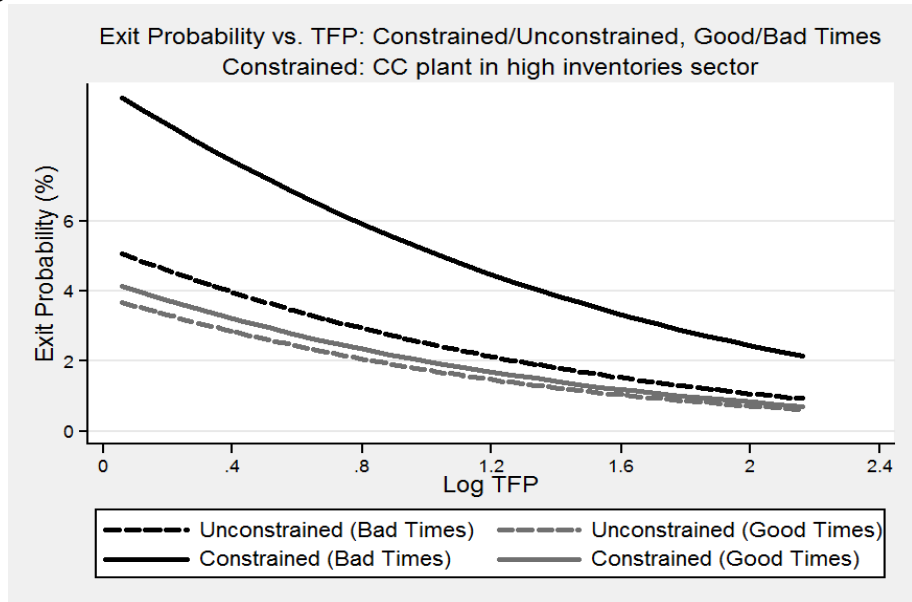
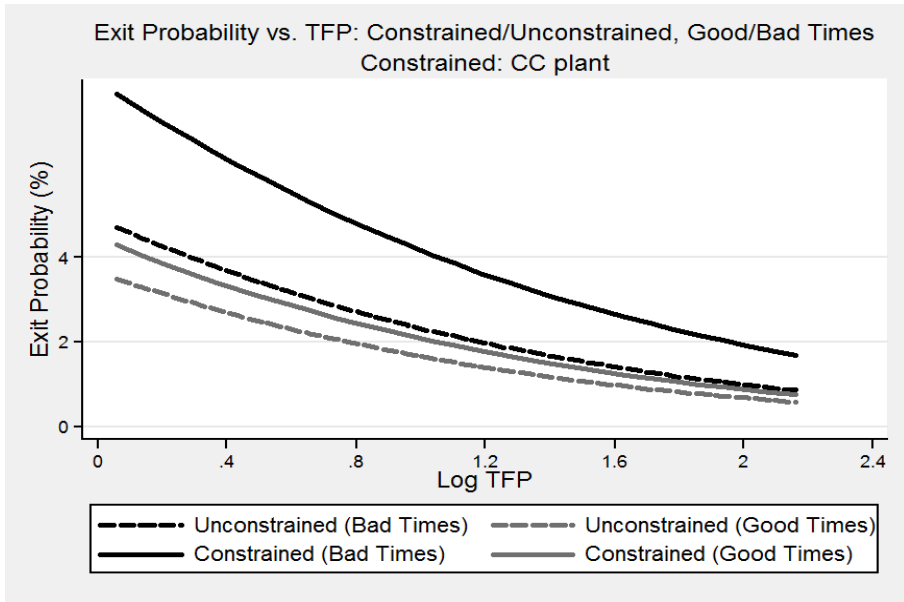


Figure 3

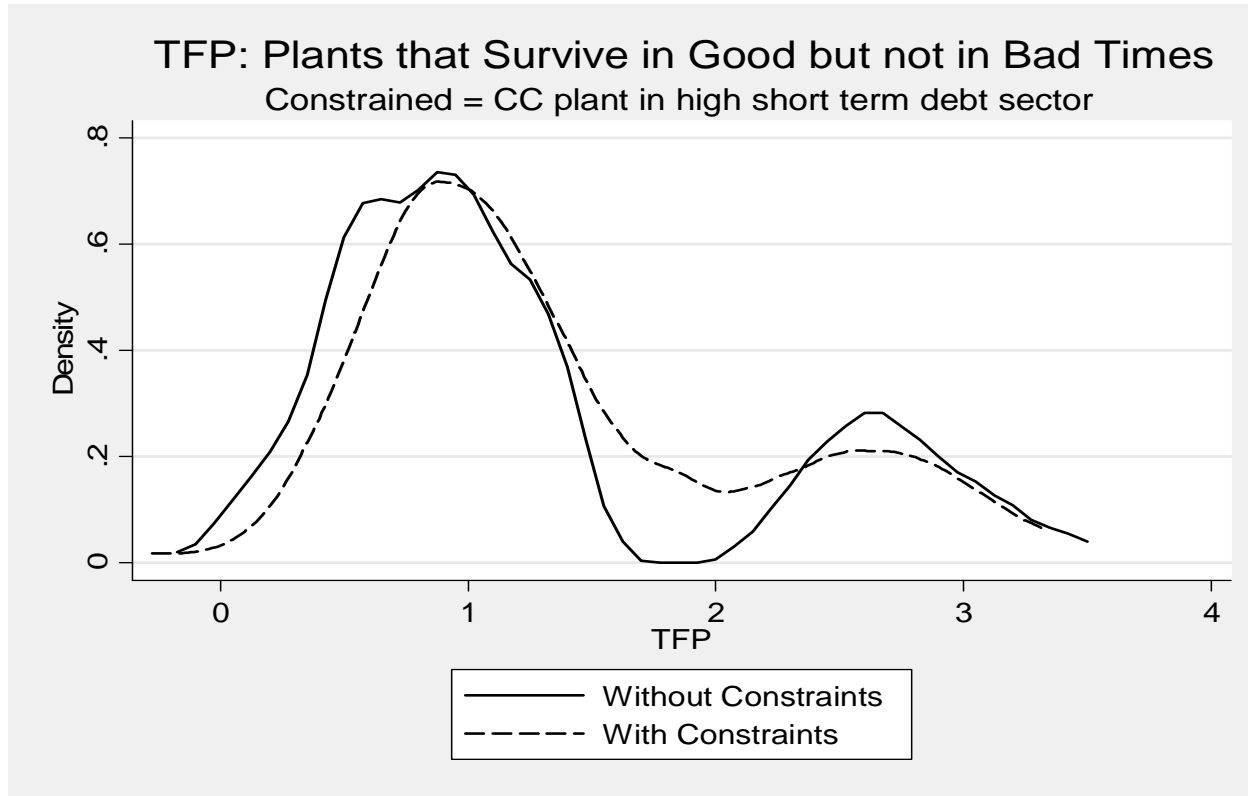


Figure 4

