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SCARRING RECESSIONS AND CREDIT CONSTRAINTS: EVIDENCE FROM COLOMBIAN FIRM DYNAMICS

Marcela Eslava, Arturo Galindo,

Marc Hofstetter and Alejandro Izquierdo[1]

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 least as high as the 39th 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.

JEL Codes: G14, L25, O47

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RECESIONES QUE DEJAN HUELLA: EL PAPEL DE LAS RESTRICCIONES CREDITICIAS

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Resumen

Usando datos de la industria manufacturera colombiana a nivel de planta entre 1995 y 2004, mostramos que las recesiones en combinación con restricciones crediticias pueden dejar cicatrices permanentes. Contrario a la literatura que enfatiza que las recesiones pueden tener efectos benéficos vía la salida de firmas poco productivas, en este artículo encontramos que firmas con restricciones crediticias se pueden ver obligadas a salir del mercado durante recesiones aun si tienen alta productividad. Por ejemplo, durante recesiones, un establecimiento con una baja PTF (percentil 10) que no enfrenta restricciones crediticias, tiene la misma probabilidad de salida que una firma con restricciones crediticias y una PTF de al menos el percentil 39. Esta brecha es mucho menor en tiempos de expansión. El artículo sugiere que las restricciones crediticias proveen una potencial explicación de los daños de largo plazo causados por las recesiones. El canal de trasmisión sugerido es la salida de firmas de alta productividad. Finalmente, el artículo provee evidencia sobre la dinámica de la salida de las firmas y su relación con el ciclo económico, un tema que la literatura había abordado principalmente desde una perspectiva teórica.

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

Clasificación JEL: G14, L25, O47.

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Introduction

In the aftermath to the recent global financial crisis, economists have been once again forced to think about the long-run consequences of short-run fluctuations. Official projections that economic activity in many developed countries will remain depressed and unemployment will remain high for several years to come have bolstered interest in studying the potential long-run damage caused by recessions.[2]

The literature has dealt with long-run implications of recessions from two complementary perspectives: the analysis of aggregate trends and the analysis of firm behavior. Focusing on the dynamics of unemployment, employment, and economic activity, studies within the former approach have found empirical evidence suggesting that recessions leave permanent or long lived scars. Meanwhile, the micro perspective has focused on how short-run fluctuations affect firm dynamics, and mostly from a theoretical standpoint. While early contributions to this branch of the literature pointed at aggregate long-run *gains* from recessions, the apparent contradictions between this view and the macro evidence have motivated recent work on crisis-times firm dynamics with potential negative aggregate consequences.

Our paper falls within the latter category of studies. We study the possibility that recessions shed some efficient producers out of the market, specifically those constrained by scant access to capital markets. We approach this question by characterizing the empirical relationship between exit, credit constraints, and productivity, using a rich dataset on Colombian manufacturing establishments. The exit of highly productive businesses has negative implications for aggregate efficiency. It may also explain long-lived effects of recessions on aggregate productivity if fixed

[2] For instance, the US' Congressional Budget Office is projecting that unemployment in the US will only return to its long run level by 2015.

entry costs make re-entry unlikely.[3] This is particularly relevant for Emerging Markets, where repeated exposure to financial crises may have led, on average, to lower aggregate productivity levels.

The fact that recessions bring long run costs to the economy has been established by a tradition of studies focusing on macro aggregates. Blanchard and Summers (1986, 1987) made the case that short run fluctuations in the unemployment rate left long lived scars on the natural unemployment rate in Europe during the 80s. They suggested an insider-outsider story: once a worker loses its job, remaining employed workers raise their wage targets, preventing the unemployed from getting their jobs back. Ball (1997) elaborated on these ideas showing that NAIRU increases during the 1980s in Europe were mainly the consequence of tight monetary policies aimed at reducing inflation. The implication was that, contrary to conventional wisdom, demand contractions alter natural unemployment rates. More recently, Ball and Hofstetter (2010) take a different look at hysteresis in unemployment by examining large changes in Latin American and Caribbean unemployment rates. They find that large increases in trend unemployment are always associated with deep recessions caused by demand contractions.

Another set of macro-level studies has focused specifically on financial crises. Abiad et al. (2009) and the WEO group (2009) look at the medium term output dynamics following banking crises. They find that, on average, although output growth does return to the pre-crisis rate, the output level remains below the pre-crises trend in the medium run. 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

[3] Dickens (1982), for instance, points at permanent productivity losses from recessions.

lack of access to financing may be one of the mechanisms preventing output recovery to its prior trend.[4]

Meanwhile, analyses of consequences of recessions on the basis of firm behavior focused for a long time on the notion that recessions may have "cleansing" effects. This tradition can be traced back to the Schumpeterian idea of creative destruction. Caballero and Hammour (1994), for instance, characterize the potential of recessions as times of cleansing, on the basis that recessions may push firms exhibiting outdated technologies out of the market.[5] 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 (e.g., Cooper and Haltiwanger, 1993; Aghion and Saint Paul, 1998).

The literature suggesting that crises have "cleansing" effects in general assumes perfect financial markets. The difficulties faced by some producers in accessing credit may partly explain the apparent contradictions between the macro empirical literature and the cleansing effects literature. Results in the macro literature pointing at financial crisis as particularly costly in the long run would be consistent with this mechanism. More tightly related, Barlevy (2003) argues that credit constraints might lead to an inefficient allocation of resources, particularly in bad times. From an empirical standpoint, firms with relatively high productivity, but which in fact are credit-constrained, may be forced out of the market during recessions. This is the mechanism that we study.

[4] Calvo, Izquierdo and Talvi (2006) provide one rationale for this behavior by showing that output collapses following financial crises are accompanied by a protracted decline in investment. The fact that investment ratios remain well below pre-crisis levels has long-run growth implications consistent with the fact that countries that have faced financial crises do not recover to pre-crisis trends.

[5] Similar results are reported in Mortensen and Pissarides (1994), among others.

More recently, Ouyang (2009) suggests another channel to explain potential scarring effects of recessions. Based on the observation that recessions disproportionally affect young businesses, her insight is 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 their cleansing effect. The mechanism we propose may be closely related to Ouyang's, since credit constraints may be one of the reasons forcing young businesses out of the market during bad times.[6] A related piece of evidence is provided by Aghion, Fally and Scarpetta (2007), who find that, conditional on survival, credit access helps new firms expand.

Our paper contributes to this literature by explicitly evaluating the role played by credit constraints in explaining firm dynamics throughout the business cycle, and by shedding light on the implied long-run consequences on efficiency. It is also the only study we know of providing micro evidence to judge the empirical merits of proposed micro foundations behind the long-run consequences of crises.

We find that credit-constrained but nevertheless high productivity units may be forced out of the market during recessions, while other less productive but unconstrained units may survive. In particular, exit probabilities for more constrained plants are significantly higher (both in a statistical and an economic sense) vis-à-vis those for unconstrained plants, throughout the set of estimations outlined below. We estimate that, during downturns, the exit probability of an unconstrained establishment with TFP at the 10th percentile is matched by that of a constrained establishment with

[6] Our paper is also related to Aghion et al. (2009). There, firms invest both in short run projects and in long-term growth enhancing projects. Countercyclical fiscal policy increases the size of the market during recessions, thus boosting the latter investment, particularly so in industries relying more on external financing. Even though their focus is on the impact of countercyclical fiscal policy, their model suggests that, in absence of such policy efforts, recessions affect investment in long-term growth-enhancing projects in credit constrained sectors.

TFP ranging from the 39th to the 86th percentile, depending on the specification. The survival premium for unconstrained businesses is much smaller during expansions. These findings indeed suggest potential scarring effects of recessions stemming from credit market imperfections. In this sense, our results are a step toward reconciling the micro and macro evidence regarding the long-run consequences of recessions. Moreover, they also add to the evidence linking credit constraints and economic development.

The rest of the paper is organized as follows. Section 2 presents our theoretical background and describes the empirical model that we estimate. Section 3 describes the data. Sections 4 and 5 present our main results and some extensions, followed by concluding remarks in section 6.

2. Theoretical framework and empirical model

Our main purpose is to explore how the probability of a firm exiting the market is affected by credit constraints, and how this relationship is altered by the business cycle. We start from the canonical model of firm exit (e.g. Hopenhayn 1992), in which a firm exits the market if the present discounted value of its nets profits falls below zero. The probability that a firm exits the market is then the probability that its expected gross profits fall below fixed operating costs. Assuming that those fixed costs follow a normal distribution, we represent the probability that a firm exits by a Probit model. In particular, we follow Eslava et al. (2009) in modeling the decision to exit in a given period *t* as a function of the determinants of current and future profitability known by the plant at time *t*.[7]

[7] Using even more detailed information on Colombian manufacturing establishments, Eslava et al. (2009) estimate a model of plant exit as a function of a detailed list of plant-level market fundamentals. The

Starting from that basic insight, we estimate a model where the probability of exiting the market at time t is a function of current total factor productivity (TFP), a measure of the size of the plant, sector and year dummies. 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. Furthermore, since we are interested in investigating whether the extent of credit-constraints faced by the plant affects its probability of exiting the market, we also include a measure of such constraints in our model.

Our basic empirical specification can be written as:

$$\Pr(x_{jt} = 1) = \Pr(\sum_{s} \alpha_s d_s + \sum_{t=t_0}^{T} \alpha_t d_t + \beta * size_{jt} + \gamma * tfp_{jt} + \sigma * constrained_j \leq u_{jt}), \quad (1)$$

where x_{jt} takes a value of 1 if plant j exits in year t, and zero otherwise; d_s are a set of three-digit sector dummies; d_t are a set of year dummies; size and TFP are measures of plant characteristics that should affect *j's* chances of surviving; $constrained_j$ is a measure of credit constraints facing plant j (defined later); and u_{jt} is a normally-distributed error term.

A word is necessary on the inclusion of size as a control in this model. In the absence of a full set of measures of fundamental determinants of exit, 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)). One possible reason for this finding is that size acts as a proxy for firm

plant characteristics they consider include TFP, demand shocks, input prices, and demand elasticities, as well as measures of trade regulations faced by the establishment. They find all of the market fundamentals they consider to matter for exit. Furthermore, they find the effect of market fundamentals to be enhanced by market reforms undertaken at the beginning of the nineties.

characteristics that theory suggests may affect exit even in the absence of frictions; for instance, idiosyncratic demand shocks are one determinant of both a firm's scale and its chances of surviving. It is under this rationale that we include size as a control in our empirical model. However, it may also be the case that size is a proxy for the effect of frictions that may affect smaller units more directly. One of those frictions 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 that extent, our estimate of σ captures the effect of being constrained beyond that of size, and 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.

Note that we are also interested in evaluating the potentially differential effects of credit constraints in good vs. bad times (defined later). Given the non-linear nature of model (1), the effect of our measure of credit constraints on the probability that plant j exits depends on the phase of the cycle, even without including explicit interaction terms between the cycle and credit constraints. More specifically, the marginal effect of a measure of credit constraints on the probability that plant j exits in period t is:[8]

$$\frac{\partial \Pr(x_{jt}=1)}{\partial constrained_j} = f\left(\sum_s \alpha_s d_s + \sum_{t=t_0}^{T} \alpha_t d_t + \beta * size_{jt} + \gamma * tfp_{jt} + \sigma * constrained_j\right)\sigma \quad (2)$$

where f is the normal density function. This marginal effect clearly depends on the specific values at which the other covariates, including the time dummies, are evaluated.

[8] Though this derivation is exact only for continuous proxies of credit constraints, the insight that the point in time at which the effect is evaluated matters also applies for discrete proxies of constraints.

We obtain the marginal effect of our measure for constraints during good times by setting the year dummies for bad years at zero, and the rest of the year dummies at the fraction of total good-times observations represented by each particular year.[9] We obtain the bad-times marginal effect in an analogous manner. Note that, with this approach, the difference in the marginal effect between good and bad times comes from the density of at-risk plants at each phase of the cycle.

Alternatively, one can also consider the potentially asymmetric effect of good vs. bad times more directly, by adding to the specification interaction terms between the measure of credit constraints and the phase of the cycle, and between these variables and TFP. Our second baseline model, summarized in equation (3), follows this approach. Here, we allow the effect of credit constraints to vary directly with good and bad times, and with TFP. In contrast with equation 1, this variation would occur even with a fixed density of at-risk units.

Our model with direct changes in the effect of credit constraints over the phase of the cycle can be written as follows:

$$\Pr(x_{jt}=1)=\Pr\left(\begin{pmatrix}\sum_s \alpha_s d_s + \beta * size_{jt} + \gamma * tfp_{jt} \\ +\sigma_1 d_{constrained,Bad\_t} + \sigma_2 d_{unc,Bad\_t} + \sigma_3 d_{unc,Good\_t} \\ + tfp_{jt} * (\kappa_1 d_{constrained,Bad\_t} + \kappa_2 d_{unc,Bad\_t} + \kappa_3 d_{unc,Good\_t}\end{pmatrix} \le u_{jt}\right) \qquad (3)$$

[9] Equivalently, we set the term :

$$\sum_{t=t_0}^{T} \alpha_t d_t$$

at a weighted average of the estimated α_t, where bad years are given a weight of zero and each good year is given a weight corresponding to the fraction of good-time observations represented by that specific year.

Here, $d_{constrained:Bad\_t}$ is a dummy with a value of 1 for observations that correspond to constrained firms in bad years, d_{unc,Bad_t} is a similar dummy for plants in unconstrained firms during bad times, and $d_{unc,Good\_t}$ is a dummy for plants in unconstrained firms during good times. Our left out category is that of plants of constrained firms during good times.[10]

3. Data

The data we use come from two separate sources. First, we use plant-level information on exit, inputs and outputs, constructed from the Annual Manufacturing Survey by Eslava et al. (2004, 2009, and 2010). Eslava et al. (2004), generate a consistent panel for 1982-1998. They have recently generated a version of the panel updated to 2004, which is the one we use. We provide below a brief description of these data (see Eslava et al, 2004 for details). A second source of information we use is the Superintendencia de Sociedades database (Supersociedades for short), which reports balance-sheet information for large firms for the period 1995-2005.

The Annual Manufacturing Survey (AMS) covers all manufacturing establishments with 10 or more employees. In the panel we use, the values of output and materials were deflated using very rich plant-level data on prices.[11] The panel also reports consumption of energy in physical units, hour-adjusted employment, and a measure of the capital stock constructed through perpetual inventory methods. We use the above listed measures of physical quantities to construct measures of TFP as log residuals from a

[10] This model does not include time dummies, which would exhibit multicolinearity with our dummies for plants in good and bad times.

[11] We do not have direct access to the plant level prices used by Eslava et al., but to the deflated quantities they calculated. Given this restriction, we do not fully replicate the very detailed exit model estimated by Eslava et al. (2009) for the period 1982-1998. This is the reason why we use size as a proxy for market fundamentals other than TFP, such as demand shocks.

KLEM production function. In calculating TFP, we use factor elasticities previously estimated by the same authors through an instrumental variable approach (Eslava et al. 2004). Following Eslava et al. (2009), we flag a plant as exiting in year t if the plant reported positive production in year t but not in year t+1.

Since the measures of physical quantities we use have been calculated with plant level prices as deflators, our measure of TFP should capture physical efficiency, or TFPQ as it has been called lately in the literature (Hsieh and Klenow, 2009; Foster et al., 2008). In absence of plant level prices to deflate output and inputs, the productivity residual (termed TFPR in absence of plant level deflators) mixes efficiency with idiosyncratic price differences. A plant with high TFPR can be a low TFPQ but high price unit. Being able to properly measure TFPQ is important in our context because while the survival of high efficiency plants is enhancing in terms of aggregate performance (arguably also in terms of welfare), the same is not necessarily true for the survival of high price plants.

As for the Supersociedades data, Supersociedades is the government office in charge of overseeing corporations. The criteria for inclusion 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, and the number and characteristics of firms included under this criterion varies substantially over time. As a result of the changing criteria for inclusion, some firms appear intermittently, while others (the largest) are included every year.

We use financial information from the Supersociedades dataset to construct our baseline measures of credit constraints. Following Hsieh and Parker (2007), we proxy for financial constraints with a dummy variable that separates firms according to their coefficients of correlation between a firm's net operating profits (a proxy for cash flows) and its purchases of fixed capital over the period for which we have Supersociedades' information. In constructing the coefficients of correlation between investment and net profits we use information on net profits from Supersociedades, and information on purchases of fixed assets (machinery, equipment, and buildings) from AMS data, adding up all plants that belong to the same firm. Our baseline measure of constraints is a dummy that takes the value of one for firms for which this correlation coefficient is in the upper third of the distribution, and zero for those firms in the lowest two thirds (as in Hsieh and Parker, 2007).

The rationale behind our proxy for credit constraints is straightforward: a firm that faces higher financial constraints is bound to rely more heavily on internal funding to finance investments, and should thus show higher correlation between investment and net profits.[12] Moreover, the use of a credit measure that is constant over time and that separates plants into constrained and unconstrained (as opposed to a continuous measure of the intensity of constraints), helps us 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. However, our measure of constraints is not affected by a firm 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

[12] See Schiantarelli (1996) and Hubbard (1998) for discussions.

of constraints only for plants that are close to the threshold we use to divide the constrained from the unconstrained.

A shortcoming of our measure of credit constraints, as noted in Schiantarelli (1996), is that current cash flows (or in our case current net profits) may be correlated with future profitability. To that extent, even unconstrained firms may rationally respond to increases in cash flows by undertaking additional investments. This has two implications for our results. First, it provides an additional reason to prefer the dichotomous measure that simply divides plants between more and less constrained, rather than trying to precisely measure the depth of constraints and their variations over time.[13] Second, we have a noisy measure of constraints, potentially implying an attenuation bias in our estimation of the effects of credit constraints. These shortcomings must be kept in mind when interpreting our results.

Given the above description, our baseline estimations are restricted to plants in the AMS that belong to firms for which there is information in the Supersociedades database. Our baseline dataset thus covers plants of relatively large manufacturing firms for the period 1995-2004.[14] The period covers the deepest recession faced by the country since the 1930s, which occurred at the end of the 1990s. Despite the mentioned data restrictions, in this baseline scenario we have 8,497 firm-year observations.

Descriptive statistics for this baseline sample are presented in Table 1, for the pooled sample (Panel A) and splitting it into observations from constrained and unconstrained firms (Panels B and C). Notice that less than 2% of the plants in this

[13] For simplicity, we will refer throughout the paper to “constrained” and “unconstrained” firms. It is, however, important to keep in mind that we are only able to divide units into “more” and “less” constrained.
[14] Though both sources have information for 2004, 2003 is the last year for which we can say if a plant survives another year or not.

sample exit the market over the relevant period; the low rate of failure is related to the focus on large firms. This focus is also reflected in an average plant size of 85 employees. Later in the paper we explore extensions of our model that allow for the coverage of smaller units.[15] It is also interesting to see that constrained firms are on average smaller in size and less productive, and that they exhibit considerably larger exit rates: 2.3% vs. 1.6%.

Finally, we split our sample into good and bad years in terms of economic activity. We use seven different criteria, from previous literature, to distinguish bad times (recessions or crises) from good times. 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. Table 2 summarizes the results. We end up identifying one period of recession (1998-2001), corresponding to the crisis period in Emerging Markets following the collapse of Russia.

4. Baseline results

a. Estimating equation (1)

Using the baseline dataset described above, we estimate model (1). Our focus is on how the exit probability depends on our credit constraint measure after controlling for TFP, size and time and sector effects. As mentioned before, the credit measure is a dummy variable equal to one for firms in the upper third of the investment-net profits

[15] Focusing on large establishments has shortcomings we discuss in further sections. It also has one advantage, however. Given our definition of exit, we may flag as exiting a plant that has not left the market but has contracted beyond the 10-employees threshold imposed by the Annual Manufacturing Survey. This is an unlikely event for a large plant.

correlation distribution. Estimation results for this specification are reported in Table 3, Panel A.

As will be the case throughout the paper, we find that smaller and less productive plants face larger chances of exiting the market. This is consistent with previous findings in the literature (e.g., Eslava et al., 2009; Bernard and Jensen, 2007). Our focus here, however, is on the role played by credit constraints, and their potentially asymmetric effects in good vis-a-vis bad times. We obtain a positive and significant coefficient for our credit constraint dummy: other things equal, establishments belonging to credit constrained firms are more likely to exit.

Given the nonlinear nature of the model we are estimating, the actual effect of credit constraints varies across observations, depending on plants' characteristics and aggregate shocks (see, for instance, the expression for the marginal effect of constraints in equation (2)). We are particularly interested in the inter-relationships between credit constraints, phases of the economic cycle, and productivity. To assess these inter-relationships, we present our results in a variety of ways—which we will replicate throughout the paper for different specifications—. First, Panel B of Table 3 presents predicted exit rates, based on our estimation of equation 1, for constrained and unconstrained plants during different phases of the cycle. Furthermore, these exit rates are evaluated at different levels of plants' TFP: the mean, the 10^{th} percentile, and the 90^{th} percentile of the TFP distribution (we call the two latter "low" and "high" TFP, respectively). In turn, Panel C shows differences between the exit rates presented in Panel B, and evaluates their statistical significance. Figure 1 evaluates the effects presented in Table 3 in a more general way, by looking at predicted exit rates over the full relevant range of TFP. Panel A of Figure 1 presents these exit rates for constrained and unconstrained plants during normal times, while Panel B differentiates between good and bad times.[16] Panel C presents differences in exit rates between constrained and unconstrained plants, separately for good times and for bad times—that is, the grey (black) line in panel C is the difference between the solid and dotted grey (black) lines in panel B—. Meanwhile, Panel D presents exit hazard differences between good and bad times, separately for constrained and unconstrained plants—the solid (dotted) line in panel D is the difference between the black and grey solid (dotted) lines in panel B—.

A first approximation at our question points at sizeable effects of constraints on firm dynamics. The gain in the probability of survival from being unconstrained is close to 0.4% for the average TFP firm during normal times (Panel A, Figure 1). This gain is large compared with the 1.8% exit rate for this sample; it is in fact equivalent to a 22 % increase in the probability of exit.

Panel A of Figure 1 further shows that the role of constraints is even more important for firms with low productivity. For a firm at the 10th percentile of the TFP productivity distribution, the gain from being unconstrained is 0.8%, compared to the 0.4% gain for the average TFP plant. The decreasing effect of constrains along the TFP distribution suggests low chances that the highest productivity units are forced out of the market due to constraints. However, we show below that the differential exit rates between the constrained and the unconstrained are sufficiently marked at crucial sections of the distribution to imply inefficient exit. Furthermore, the finding that the effect of constraints decreases markedly with TFP is not constant across the different specifications and samples we evaluate below.

[16] The evaluation of effects in good vs. bad times is explained in footnote 9. Exit rates during "normal times" are estimated by setting each of the time dummies at the fraction of total observations represented by the respective year.

We are obviously also interested in understanding the role of the business cycle in this story (Panel B in Table 3 and Figure 1). We find that exit is more likely during recessions for plants of all productivity levels, supporting the view that downturns are times of increased restructuring. Moreover, we continue to find a positive and significant effect of belonging to a firm in the upper third of the constraints distribution: firms that we flag as more constrained face a larger chance of exiting the market, at any level of TFP. Most interesting, this effect is larger during bad times. In particular, moving from unconstrained to constrained status during bad times increases the probability of exiting the market by 0.6% for the average TFP plant (or a 40% rise in the probability of exit); the figure drops to 0.3% during good times.[17] Differences between constrained and unconstrained units decrease with increases in TFP, for both good and bad times (Panel C, Figure 1). Similarly, the negative effect of bad times on firms' chances to survive diminishes as TFP goes up.[18]

These findings imply an aggregate inefficiency coming from financial constraints: constrained firms exit the market even when they are sufficiently productive to have survived in the absence of constraints. Put differently: some firms exit while being more productive than others that survive, solely because they face financial constraints. Though the positive effect of financial constraints on exit decreases with the level of TFP in this estimation, we shall see below that more flexible specifications show differences in this pattern over the cycle.

b. Estimating the model with interactions (Equation (3))

[17] Both differences are significant at the 10 percent level (Panel C, Table 3).

[18] Others have also found that negative shocks affect more productive firms less strongly, in different contexts. For instance, Bloom et al. (2009) find that an increase in imports from China affects the chances of survival by European firms, but that the effect decreases with firms' TFP.

The model in Table 3, although non-linear by nature given the use of a Probit specification, ignores the possibility that the effect of credit constraints depends on the phase of the economic cycle, even for a given density of at-risk plants. In this subsection, we look at a more flexible model with explicit interactions (Equation (3)). The model includes interaction terms between TFP, the credit constraints dummy, and good and bad time dummies. The results from this estimation are presented in Table 4 and Figure 2 (following the same formats and conventions of Table 3 and Figure 1, respectively.)

Looking at normal times (Panel A, Figure 2) we continue to find that credit constraints increase the probability that a plant exits. We also find that this effect varies considerably over the cycle and over the TFP distribution. For the average plant in terms of TFP, the increase in exit probability from being constrained is 0.9% in bad times and 0.2% in good times (Panel B, Table 4). Moreover, it is statistically significant only in bad times. The flip side of this relationship is that bad times hit constrained firms much harder than unconstrained firms. The difference is starker than in the results from the less flexible specification in Equation (1). For an average TFP firm, moving from good to bad times increases the exit rate by 0.7% for unconstrained firms. The figure is *twice* as large for constrained firms. The increased probability of exiting during recessions relative to good times is statistically significant for both constrained and unconstrained firms.

Compared with the model without interactions, the quantitative differences are evident. For instance, note the large difference between good and bad times in terms of the survival probability premium for unconstrained firms (Panel C in Table 4 and Figure 2). For an average TFP plant, this premium is over four times larger in bad times compared to good times (0.9% vs. 0.2%). In contrast, in the model presented in Table 3, the bad times premium only doubled that of good times. These results suggest that the direct interaction between credit constraints and the business cycle should not be ignored. Both the role of credit constraints and that of the business cycle are boosted in this less restrictive specification.

To grasp the potential scarring effects of recessions implied by these findings, we build the following counterfactual. We take the predicted exit probability of an unconstrained firm with low TFP (10th percentile), and estimate what TFP level would leave the exit probability unaltered if the firm were to move from unconstrained to constrained status. Results suggest that, during bad times, TFP would have to increase to that of the 39th percentile in order to leave the exit rate unchanged. The same statistic for good times is a move in TFP to the 17th percentile. In other words, during bad times, moving from unconstrained to constrained status has a quantitative effect equivalent to reducing productivity from the 39th percentile to the 10th. We see this as strong evidence of scarring effects of recessions operating through financial constraints.

The results reported so far on the effects of credit constraints are a lower bound of their actual role, for two reasons. On the one hand, the regressions are controlling for the size of the firms, a variable that has been often used to capture credit constraints. That is, some of the effect we want to estimate is actually captured through the firm size variable. On the other hand, we are focusing on a sample of large firms, i.e., a sample with firms that are all likely to have some degree of access to credit. We address concerns arising from these issues in the next section.

5. Expanding the Dataset

As discussed above, one problem with our measure of credit constraints is that it is based on balance-sheet information, available only for large firms. As such, we are identifying the effects we are interested in out of the limited variation in the degree of credit access across large firms. Moreover, we are focusing on a set of establishments that are probably not the key target group when interested in the effects of credit constraints. This is a problem that plagues the literature on financial constraints, since balance-sheet information is generally available only for large firms, in some cases even only those firms that are publicly listed.

Given the central interest on smaller establishments we try to overcome this limitation in this section by bringing in smaller establishments present in the Annual Manufacturing Survey but not in the Supersociedades data. We overcome the difficulty of not having access to financial information for the firms that own these establishments by using information on the size of the establishments. Our departing point, consistent with several papers in the literature (e.g., Gertler and Gilchrist, 1994) is that small units are more likely to be credit constrained. We thus add to our previous sample all establishments belonging to firms that do not report to Supersociedades, and code small establishments as being constrained. We define "being small" as having 20 or less employees on average over the period for which we observe the establishment in the AMS.[19] The rationale for proceeding in this manner is to define as constrained only establishments for which we are fairly sure their level of access to credit is much lower than that of plants owned by firms that we code as unconstrained. Note, for instance, that the 20 employees mark is significantly lower that the 25th percentile in terms of

[19] Establishments with 20 or less employees are close to a third of the firms for which we have Annual Manufacturing Survey information. Our measure of labor comes from the Annual Manufacturing Survey, so we only have employment in the manufacturing activities of the unit.

employment for the baseline sample (even lower when compared to the subsample of unconstrained plants in the baseline, see Table 1). For completeness, we also add firms in the AMS with more than 20 employees that do not report to Supersociedades, but consider them to be unconstrained given that they surpass the 20 employee cut-off point.[20]

Descriptive statistics of our variables of interest for this expanded sample are shown in Table 5. Note that the time frame used here is the same as in the previous section. The exit rate for this expanded sample is above 7%, a much higher rate when compared to the less than 2% exit rate for the larger firms in our baseline case. It is also worth pointing at the reduction in the average number of employees in this sample (approximately 29 employees), compared to our baseline (approximately 85 employees). Average TFP has also gone down, though only by 7 log points.

Table 6 presents results of re-estimating equation (3)--our preferred specification--for this expanded sample.[21] As before, Panel A reports regression results and Panel B selected predicted exit rates. While most results are qualitatively analogous to those discussed above, the role of credit constraints appears larger. For a plant with average TFP, moving from unconstrained to constrained status during bad times *doubles* the exit rate, from 4.2% to 8.6% (Panel B, Table 6). This absolute increase of 4.4 percentage points is much larger than the corresponding increase in the chances of exiting during good times: only 2 percentage points (Panel C of the same Table). Moreover these survival premiums for unconstrained plants are much larger than those observed in Table 4, and they are significant at the 1% level. Interestingly, there is no significant

[20] This assumption, if anything, should play against finding effects of credit constraints, as there is a risk that some of these firms could indeed be constrained.

[21] As noted before, added plants are split into constrained plants with a size of 20 employees or less, and unconstrained plants with a size of more than 20 employees.

increase in the probability of exit of unconstrained plants between good and bad times, whereas there is a significant increase (of 2.2 percentage points) in the probability of exit for constrained plants. It thus seems that unconstrained plants are better able to cope with shocks than constrained plants. Both the large survival premium for constrained plants and the very marked differences between bad and good times are replicated at all levels of TFP (Panels C and D, Figure 3.)[22]

Our findings in this section imply even larger potential costs of financial constraints, in terms of aggregate efficiency, than our findings in previous sections. Consider, for instance, the counterfactual of the previous section: for an unconstrained but low TFP (10th percentile) firm, we estimate the exit hazard and then calculate the increase in TFP necessary to leave this hazard unaltered when switching to constrained status. The result is a move to the 86th percentile of TFP during bad times and to the 42nd percentile in good times. Even more worrisome in terms of aggregate efficiency, however, is how the combined effect of constraints and recessions varies over the distribution of TFP in this sample. While for the Supersociedades sample the bad times increase in a constrained plant's probability of exiting was much lower for high productivity plants than for low probability ones, the same is not the case for this sample with smaller plants. High productivity constrained plants face a similar increase in their chances of exiting during a recession than low productivity plants (Panel B, Table 6). This suggests that, contrary to the case of large firms, small units have a harder time insuring against the effects of credit constraints by becoming highly productive.

[22] Moreover, formal tests of the differences in exit probabilities between good and bad times for constrained vis-à-vis unconstrained firms measured at average TFP levels are significant at the 1% level. In other words, differences in the curves shown in Panel D are significant at the 1 % level.

Despite these revealing results, a word of caution is warranted. Credit constraints are much more loosely measured in Table 6 than in our baseline exercises. Moreover, by adding size to the definition of constraints, the current extension partially mixes in an effect that we were separating in our previous exercises. Adding these facts to the change in sample, it is clear that results in this section are not fully comparable to those in Tables 3 and 4. It is still interesting to point out that, after adding the smaller and lower-TFP plants that we consider in this sample, we find increased potentially scarring effects of recessions.

6. Concluding remarks

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. With a reduced sample but an accurate measure of credit constraints (Table 4), this difference is nearly 0.9 percentage points for the average TFP plant, equivalent to a 60 percent increase in the exit rate (the exit rate for unconstrained firms in bad times is 1.5%). In good times, this difference is cut to 0.2 percent, or a 25% increase in the exit rate. Alternatively, in a specification with a larger sample but incorporating a looser credit constraint definition, this difference is 4.4 percentage points in bad times−or an increase of 105 percent in the exit rate relative to that of unconstrained firms in bad times−and 2 percentage points in good times−or an increase of 46 percent in the exit rate.

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 a negative impact on aggregate TFP. Moreover, the losses may translate into long-term scars to the extent that re-entry is unlikely due to high entry costs. In this sense, the evidence we have presented helps reconcile aggregate trends 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, 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.[23] 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

[23] See Galindo and Schiantarelli (2003) for a discussion of credit constraints and firms in Latin America.

value implicit in the still fragile relationships some of the exiting plants may have created with the financial system.[24]

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, financial reform intended 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.

[24] Since our indicator for constrained businesses only indicates more limited credit access relative to other businesses in our sample, it is still possible that some plants we classify as constrained have established ties with financial institution. These ties, however, should be relatively weak (and probably young.)

Appendix

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.

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Table 1. Descriptive Statistics

Panel A. Baseline case (1995-2004)

	(1)	(2)	(3)	(7)	(8)	(9)
	N	Mean	S.D.	P25	P50	P75
Exit Dummy	8,497	0.0182	0.1338	0	0	0
TFP	8,497	1.3057	0.9205	0.7518	1.2265	1.7613
Dummy for Constrained Firms	8,497	0.3029	0.4596	0	0	1
Log Labor	8,497	4.4428	1.1622	3.7612	4.4543	5.1930

Panel B. Baseline case for constrained plants (1995-2004)

	(1)	(2)	(3)	(7)	(8)	(9)
	N	Mean	S.D.	P25	P50	P75
Exit Dummy	2,574	0.0233	0.1509	0	0	0
TFP	2,574	1.2854	0.9971	0.7313	1.2009	1.7429
Log Labor	2,574	4.3922	1.1307	3.6889	4.4427	5.1417

Panel C. Baseline case for unconstrained plants (1995-2004)

	(1)	(2)	(3)	(7)	(8)	(9)
	N	Mean	S.D.	P25	P50	P75
Exit Dummy	5,923	0.0160	0.1256	0	0	0
TFP	5,923	1.3145	0.8851	0.7632	1.2385	1.7654
Log Labor	5,923	4.4648	1.1751	3.8067	4.4659	5.2149

Note: Dummy for Constrained Firms is 1 if the plant is in the upper third of the correlation between investment and net profits.

Table 2. Years of Recession (Bad times)

Negative annual per capita GDP growth	1998, 1999, 2001
Negative annual per capita GDP growth	1999
Trough to peak strategy	1998, 1999, 2000, 2001, 2002
Two or more quarters with negative GDP growth	1998, 1999
Sudden Stop	1998, 1999, 2000
Banking Crisis	1999, 2000, 2001
Years with cyclical component below 1 std devation	1999, 2000, 2001, 2002, 2003, 2004
Years that satisfy at least four criteria	1998, 1999, 2000, 2001

Table 3. Exit Probability as a Function of Credit Constraints

Panel A. Probit Estimations

TFP	-0.2751***
	(0.0472)
Log Labor (t-1)	-0.1680***
	(0.0331)
Dummy for Constrained	0.1432**
	(0.0727)
Constant	-1.5548***
	(0.2694)
Sector Effects	YES
Time Effects	YES
Observations	8,497

Panel B. Predicted Exit Rates

	Low TFP	Mean TFP	High TFP
Unconstrained, bad times	2.9%	1.5%	0.7%
	(0.4%)***	(0.2%)***	(0.2%)***
Constrained, bad times	4.0%	2.1%	1.0%
	(0.7%)***	(0.4%)***	(0.3%)***
Unconstrained, good times	1.3%	0.6%	0.3%
	(0.3%)***	(0.2%)***	(0.1%)***
Constrained, good times	1.9%	0.9%	0.4%
	(0.4%)***	(0.2%)***	(0.1%)***

Panel C. Exit rate differentials (Mean TFP)

Constrained - Unconst. (Bad times)	0.6%
	(0.3%)*
Constrained - Unconst. (Good times)	0.3%
	(0.2%)*
Bad - Good times (Unconstrained)	0.9%
	(0.2%)***
Bad - Good times (Constrained)	1.2%
	(0.3%)***

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Dummy for Constrained Firms is 1 if the plant is in the upper third of the correlation between investment and net profits. Low and High TFP are respectively the TFP values at the 10th and 90th percentile of the plant TFP distribution.

Table 4. Interacted Model

Panel A. Probit Estimations

TFP	-0.2547***
	(0.0787)
Log Labor (t-1)	-0.1723***
	(0.0323)
Unconstrained* Bad Times	0.1661
	(0.1502)
Constrained * Bad Times	0.3622**
	(0.1692)
Unconstrained * Good Times	-0.0615
	(0.1467)
TFP * Unconstrained * Bad Times	-0.0197
	(0.1154)
TFP * Constrained * Bad Times	(0.0153)
	(0.1293)
TFP * Unconstrained * Good Times	-0.0139
	(0.1069)
Constant	-1.0828***
	(0.1852)
Sector Effects	YES
Time Effects	NO
Observations	8497

Panel B. Predicted Exit Rates

	Low TFP	Mean TFP	High TFP
Unconstrained, bad times	2.9%	1.5%	0.7%
	(0.5%)***	(0.3%)***	(0.3%)**
Constrained, bad times	4.5%	2.4%	1.2%
	(1.0%)***	(0.5)%***	(0.5%)**
Unconstrained, good times	1.7%	0.8%	0.4%
	(0.3%)***	(0.2%)***	(0.1%)***
Constrained, good times	2.0%	1.0%	0.5%
	(0.5%)***	(0.3%)***	(0.2%)**

Panel C. Exit rate differentials (Mean TFP)

Constrained - Unconst. (Bad times)	0.9%
	(0.5%)*
Constrained - Unconst. (Good times)	0.2%
	(0.3%)
Bad - Good times (Unconstrained)	0.7%
	(0.3%)**
Bad - Good times (Constrained)	1.4%
	(0.5%)***

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Dummy for Constrained Firms is 1 if the plant is in the upper third of the correlation between investment and net profits. Low and High TFP are respectively the TFP values at the 10th and 90th percentile of the plant TFP distribution.

Table 5. Descriptive Statistics for the expanded dataset

	(1)	(2)	(3)	(7)	(8)	(9)
	N	Mean	S.D.	P25	P50	P75
Exit Dummy	31,024	0.0704	0.2558	0	0	0
TFP	31,024	1.2116	0.9850	0.5927	1.1346	1.7303
Dummy for Constrained Firms	31,024	0.4815	0.4997	0	0	1
Log Labor	31,024	3.3821	1.3172	2.4849	3.2581	4.2485

Notes: Dummy for Constrained Firms is 1 if the plant is in the upper third of the correlation between investment and net profits for establishements reporting in AMS as well as in Supersociedades, or if the plant has less than 20employees. For plants with 20 of more employees reporting in AMS but not in Supersociedades the Dummy for Constrained Firms is zero.

Table 6. Interacted Model Using the Extended Dataset

Panel A. Probit Estimations

TFP	-0.1990***
	(0.021)
Log Labor (t-1)	-0.1809***
	(0.011)
Unconstrained* Bad Times	-0.2251***
	(0.055)
Constrained * Bad Times	0.1190***
	(0.041)
Unconstrained * Good Times	-0.1665***
	(0.048)
TFP * Unconstrained * Bad Times	0.0181
	(0.039)
TFP * Constrained * Bad Times	0.0334
	(0.030)
TFP * Unconstrained * Good Times	-0.0164
	(0.036)
Constant	-0.7891***
	(0.045)
Sector Effects	YES
Time Effects	NO
Observations	31,024

Panel B. Predicted Exit Rates

	Low TFP	Mean TFP	High TFP
Unconstrained, bad times	6.3%	4.2%	2.6%
	(0.5%)***	(0.3%)***	(0.3%)***
Constrained, bad times	11.8%	8.6%	5.8%
	(0.6%)***	(0.4%)***	(0.4%)***
Unconstrained, good times	7.0%	4.3%	2.4%
	(0.5%)***	(0.2%)***	(0.3%)***
Constrained, good times	9.6%	6.4%	3.8%
	(0.5%)***	(0.3%)***	(0.3%)***

Panel C. Exit rate differentials (Mean TFP)

Constrained - Unconst. (Bad times)	4.4%
	(0.5%)***
Constrained - Unconst. (Good times)	2.0%
	(0.4%)***
Bad - Good times (Unconstrained)	-0.2%
	(0.3%)
Bad - Good times (Constrained)	2.2%
	(0.4%)**

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Dummy for Constrained Firms is 1 if the plant is in the upper third of the correlation between investment and net profits for establishements reporting in AMS as well as in Supersociedades, or if the plant has less than 20 employees for establishements only reporting in AMS. For plants with 20 of more employees reporting in AMS but not in Supersociedades the Dummy for Constrained Firms is zero.

Figure 1: Baseline model

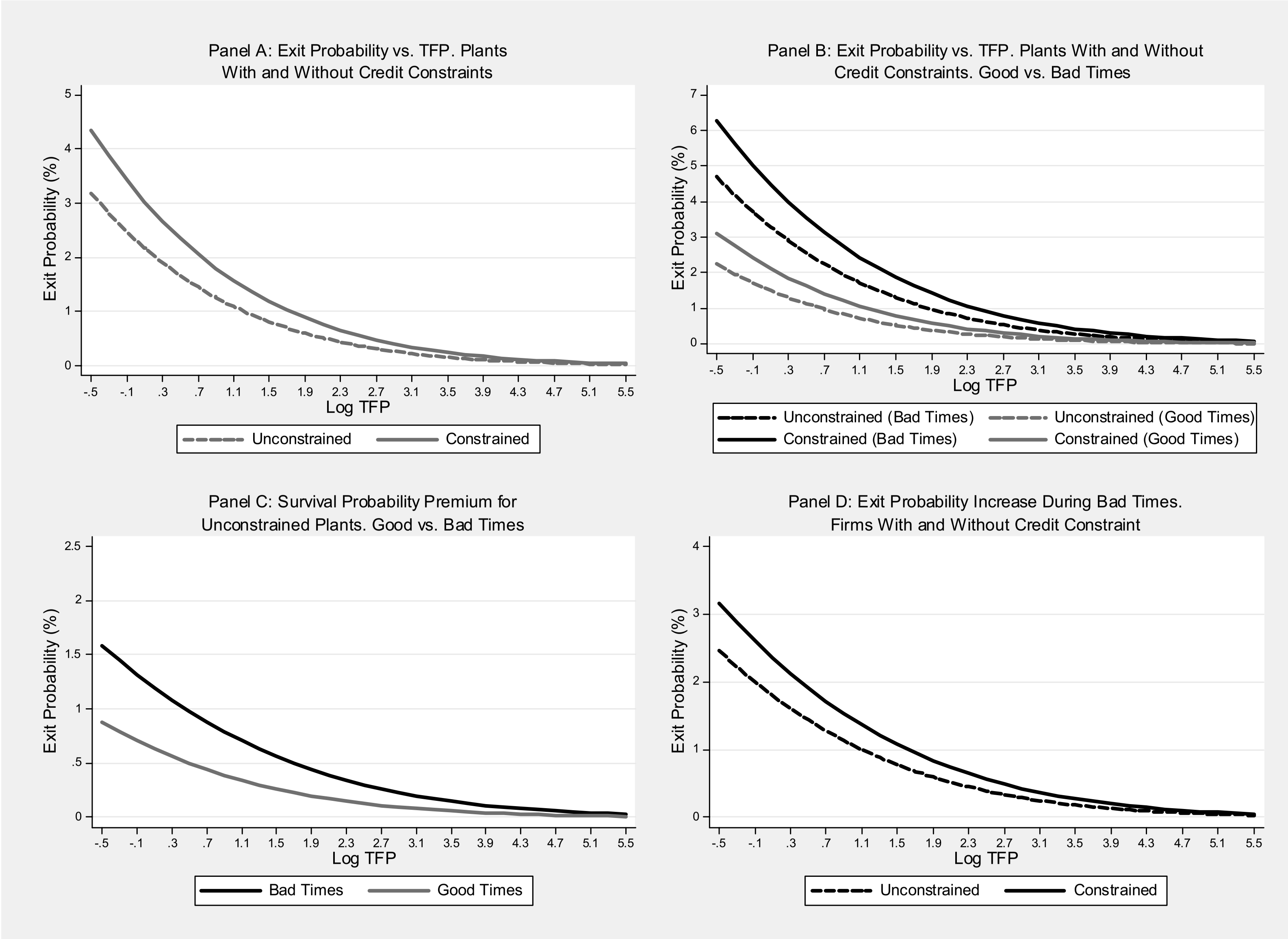

Figure 2: Baseline interacted model

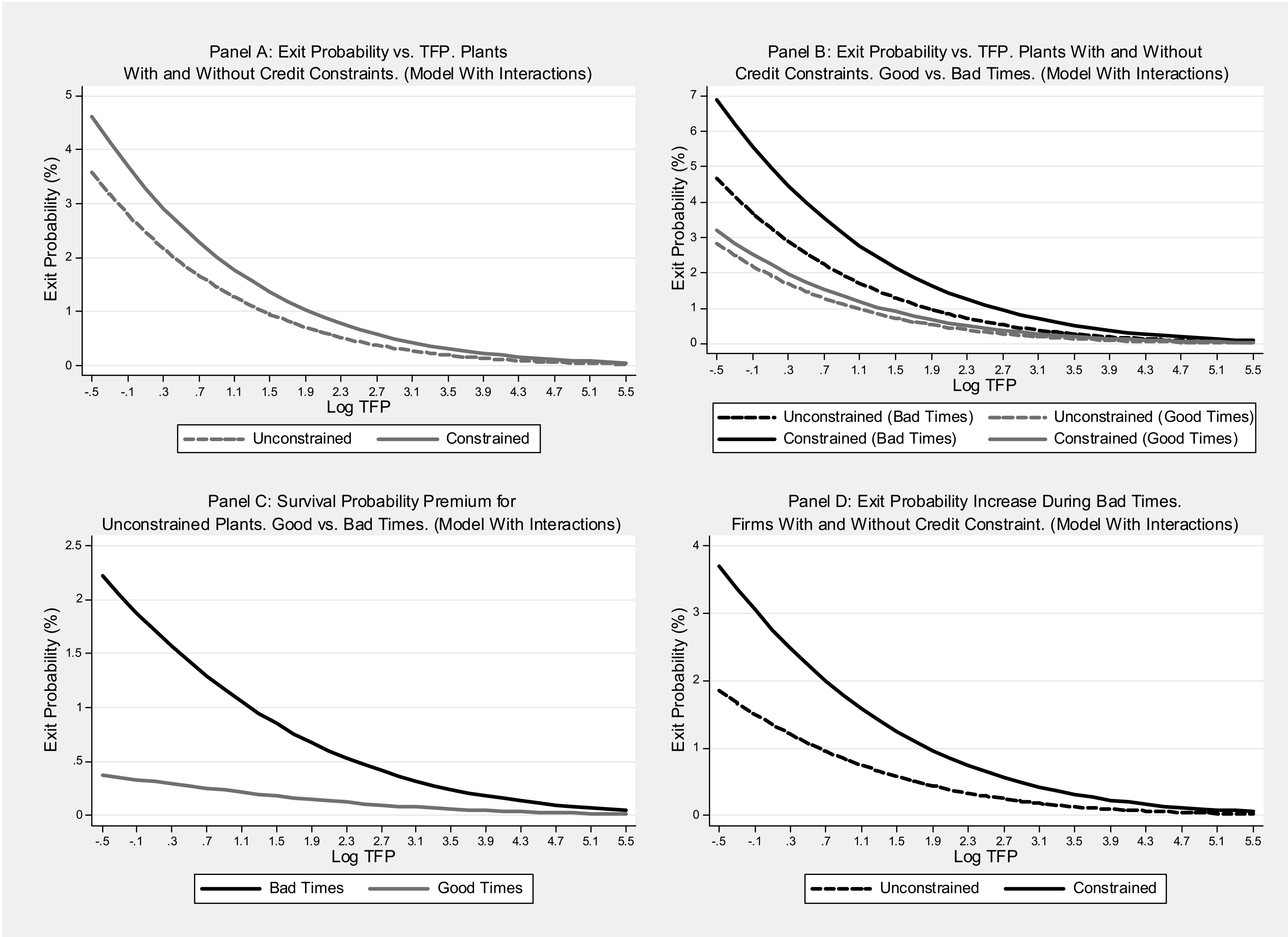

Figure 3. Extended Dummy of Credit Constraints