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One Size Does Not Fit All: TFP in the Aftermath of Financial Crises in Three European Countries

Abstract

We analyse the impact of both the Global Financial Crisis of 2008 and the European sovereign and banking crisis of 2011-13 on firm-level productivity in France, Italy and Spain. We show that relying on a single break date in 2008 misses both the Eurozone crisis and countries' institutional specificities. Although leverage and financial constraints affect firm-level productivity negatively, high-leverage firms suffer more from financial constraints only in Italy, when they are relatively small or when their debt is of short maturity. These results call for approaches taking into consideration country-level characteristics of financial institutions and time varying financing constraints of the firms, instead of pooling data and adopting a common break date. One size does not fit all when it comes to identifying the impact of financial crises on firm level productivity.

JEL Codes: E220, E230, E440, D240.

Keywords: total factor productivity, firm-level data, financial constraints, crises.

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1 Introduction

Various explanations of the productivity slowdown observed in advanced economies since the mid 1990s have been proposed. Slower diffusion of innovation, factor misallocation, market structures, ageing, skills, slowing international trade integration and firms mis-management are among the structural determinants of such slowdown. But beyond those, the contribution of the 2008 Global Financial Crisis (GFC) and of its legacy is at stake: the GDP cost of a recession is especially marked and long-lasting when the recession is associated with a financial crisis (Cerra and Saxena, 2008, Blanchard, Cerutti and Summers, 2015; Romer and Romer, 2017). Such evidence falls in sharp contrast with the Schumpeterian creative destruction hypothesis according to which recessions should have a "cleansing effect", i.e. eliminate the least-productive firms and positively impact long-term Total Factor Productivity (TFP) (Davis and Haltiwanger, 1992; Caballero and Hammour, 1994).

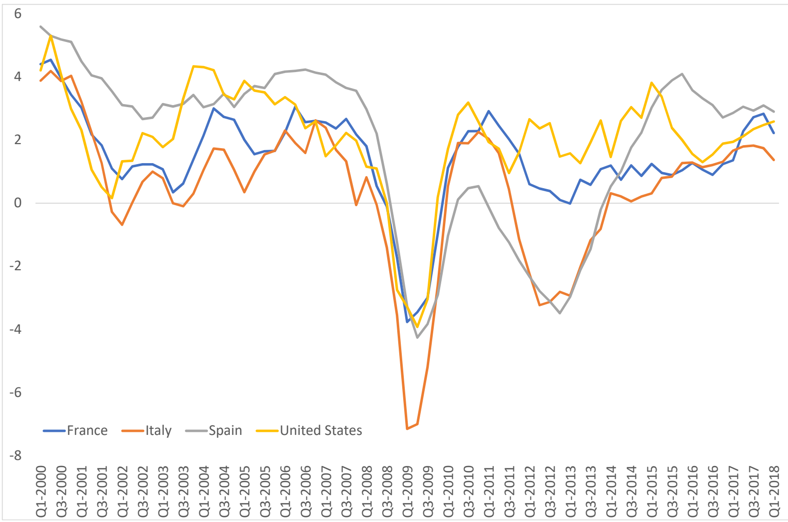
There are many reasons why a sharp recession may not help redirecting resources towards the most efficient firms: jobs created during recessions are of low quality ("sullying effect", Barlevy, 2002); firms with the highest potential in terms of productivity are destroyed during recessions ("scarring effect", Ouyang, 2009); lastly, creations and destructions may well slow down during the recovery (Caballero and Hammour, 2005). All in all, frictions may hamper the reallocation of resources towards the most promising businesses during a crisis, and credit frictions are indeed the usual suspect (Barlevy, 2003). Companies in financially-dependent sectors tend to perform worse after the crisis (Paz-Pardo, 2016); high-leveraged or highly indebted firms have experienced slower TFP growth after the GFC – but not after the recession of 2001 (Duval et al., 2020); high-leverage firms had on average a significantly lower investment rate than before crisis (Kalemli-Özcan et al., 2018); firms with weaker balance sheets invested less in intangibles capital after the GFC, especially in those countries with more credit tightening (Ahn et al., 2018).[1]

The shock of the GFC – a deep crisis with a prominent financial component – may help sorting out these different channels through a difference-in-difference methodology. Our point is however that considering 2008 as the date break raises two issues. First the concept of "post-crisis" is misleading for European countries having suffered another deep crisis in 2011-13 (Figure 1). Second, focusing on the potential credit channel, the heterogeneity of national patterns is

[1] Aghion et al. (2018) propose theoretical underpinnings of reduced investment in illiquid projects such as R&D during recessions.

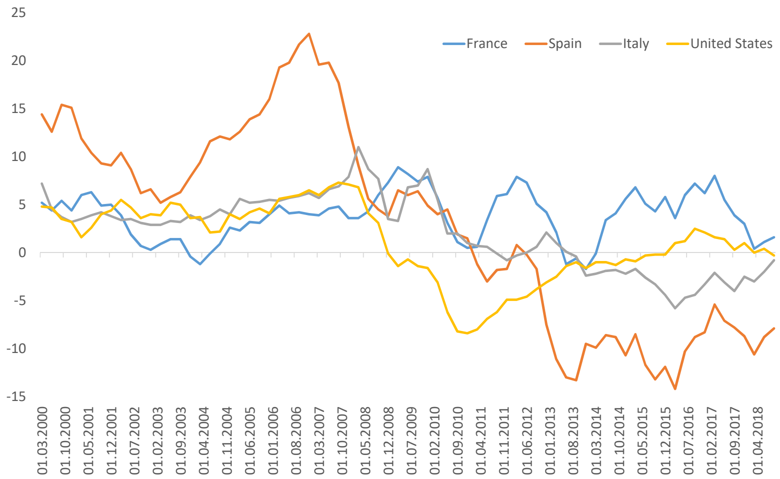
evident. In Figure 2 we plot the year-on-year variation of the credit-to-GDP ratio for the United-States, France Italy and Spain. In the United-States, the ratio decelerates in 2008 and falls in 2009-12, before stabilizing. In Spain, credit-to-GDP decelerates already in 2007 from a much higher year-on-year variation, bottoms out in 2014-15 and recovers only partly afterwards. In comparison, the evolution is much milder in Italy while in France, there is hardly any credit crisis at all. Hence, comparing the evolution of TFP pre- and post-GFC in a pool of OECD countries cannot provide clear answers on how economic and/or credit crises affect TFP: One size does not fit all. Our contribution is to revisit the financial channel of transmission of the recession to TFP using a different approach in terms of identification.

Figure 1: Real GDP growth: year-on-year variation in percent



Source: OECD.

Figure 2: Credit to GDP: year-on-year variation in percentage points



Note: Credit from all sectors to private non-financial sector.
Source: Bank of International Settlements.

We concentrate on the three large euro-area countries already mentioned and combine information at the microeconomic level about firms and their balance sheets, with macroeconomic indicators of financial conditions. While sharing the same currency and the same regulatory environment, France, Italy and Spain have been hit by very different credit shocks and have behaved quite differently since the GFC.[2] In order to shed light on the issues raised by the conventional approach, we start by estimating the impact of the GFC using a post-GFC dummy. As said, this identification strategy is not expected to provide satisfactory results for two reasons: presence of a second break date – 2001-13 for Italy and Spain – in the euro-area, and idiosyncratic differences in national financial institutions (e.g. firm-banks relationships).

In a second step, we tentatively sort out the country-specific channels of transmission from the financial to the real sphere by estimating the impact of various measures of financial conditions on TFP. Investment is certainly the key variable when it comes to consider a long-standing effect on productivity of a temporary shock. Firms can finance their TFP growth (i.e. R&D, technology adoption, re-organization, re-training, etc.) with cash flows, equity or debt. Here we focus on the borrowing channel and study whether lagged leverage makes a firm more vulnerable

[2]We exclude non-euro area countries in order to limit the heterogeneity of our sample, and Germany is not covered in our sample due to data limitations.

to credit tightening, once the other funding sources are controlled for through firm-level cash-flows and sector-time fixed effects, the latter controlling for equity prices at the sector level. We find that, although leverage has a negative impact on TFP in all three countries, this impact is magnified by credit restrictions only in Italy.

Our contribution is to highlight the heterogeneity of the TFP reaction to credit constraints. Country determinants matter. Instead of investigating the link between the growth of credit and TFP, we focus on variations in financial fragility, credit tightness and TFP. Lagged firm-level leverage is accordingly envisaged as a fragility. Because we regress the level of TFP on firm-level controls, control for firm-level cycle, measure leverage as deviations within size bins and control for a range of fixed effects, we are able identify the determinants of deviations of TFP from sector-time specific and firm-specific averages. We confirm that both leverage and financial constraints hamper TFP. But interestingly, only in Italy do high-leverage, small firms suffer more from financial constraints. Various robustness checks confirm that our results are not driven by selection biases or reverse causality.

The remainder of the paper is organised as follows. Section 2 briefly surveys the related literature. Section 3 describes the dataset. The impact of leverage on TFP after the GFC is presented in Section 4. In Section 5, we estimate the impact of country-specific credit conditions on TFP. Section 6 provides a series of robustness checks and Section 7 concludes.

2 Related literature

The literature studying the impact of financial conditions on aggregate TFP can be organized around a distinction between the extensive margin of TFP growth (i.e. higher productivity firms substituting for lower-productivity ones) and its intensive margin (i.e. incumbent firms upgrading their own TFP). Although somewhat simplistic (since a given firm may be understood as a collection of plants or businesses), this divide is convenient from a methodological point of view.

2.1 Extensive margin

The key mechanism for the extensive margin is the cleansing effect: during a financial crisis, the less-productive firms are kicked out of the market, which makes TFP improve after the crisis. However, an efficient reallocation of resources implies a combination of exits and entries. The latter may be impaired by the inability of the financial system to carry out an efficient capital reallocation during a crisis (Osotimehin and Pappadà, 2017). US data from the mid-1970s through 2011 suggests limited factor reallocation during the GFC as a result of a weakening of the cleansing effect (Foster et al., 2016). In addition, those US regions with less regulatory forbearance during the GFC experienced more reallocation and stronger productivity growth after the crisis (Gropp et al., 2017). Ultimately there is evidence of a large increase in factor misallocation during the GFC (Di Nola, 2017). As for Italy, banks with less capital lent more to firms with higher leverage and lower return on assets during the crisis (Schivardi et al., 2017).

The impact of interest rates on resource allocation, is another channel of transmission, in relation with firm-level leverage. The slowdown of TFP growth in Southern Europe between 1999 and 2012 has been interpreted as a consequence of the fall in real interest rates in relation with European monetary union (Gopinath et al., 2017): only financially unconstrained firms (with relatively high net worth) have benefited from lower interest rates through higher borrowing, but they were not necessarily the most productive firms, hence triggering capital misallocation. Likewise, monetary easing as a response to the European crisis may have had detrimental impact on TFP growth by allowing "zombie firms" to survive without promoting the growth of healthy firms.[3] This is the "whatever it takes" syndrome whereby increased credit supply finances low-quality borrowers, i.e. firms with below-median interest coverage.[4]

2.2 Intensive margin

The intensive margin plays a key role for aggregate TFP (Hsieh and Klenow, 2018) and financial constraints shape this margin through reduced investment in physical capital, technology adoption and R&D.

The speed of technology adoption is pro-cyclical and highly dependent on firm's cash-flow (or profit), which signals credit constraints (Canepa and Stoneman, 2005; Anzoategui et al., 2019). Investment in R&D is pro-cyclical in presence of credit constraints, especially in sectors that are highly reliant on external finance (Aghion et al., 2012). This is consistent with the limited pledgeability of intangible capital. Financial constraints are a key determinant of R&D activities and exports, as evidenced by a survey in five European countries in 2008 (Altomonte et al., 2015). These results are confirmed by the survey of 1,050 chief financial officers in different

[3] Zombie-lending was first discussed by Caballero et al. (2018) in the context of the Japanese lost decade.

[4] With reference to the famous statement of President Draghi in July 2012, followed by the announcement of Outright Monetary Transactions, see Acharya et al. (2019).

countries in December 2008: there is a link between their self-declared financial constraints and cuts in tech spending, employment and capital spending, with widespread recognition of missed investment opportunities (Campello et al. , 2010).

The slowdown of TFP in OECD countries after the GFC is more pronounced for firms that displayed weaker balance sheet prior to the crisis, and also in countries with tighter financial constraints as measured through changes in average bank CDS spreads (Duval et al., 2020). Considering also firm-bank relationships, Kalemli-Özcan et al. (2018) estimate the impact of pre-2008 debt overhang on post-2008 net investment rate in euro-area countries. They show that higher pre-crisis leverage reduces post-crisis investment, especially in those firms whose banks are "weaker" in the sense of being more exposed to domestic sovereign debt. Working on US data, De Ridder (2016) finds that higher exposure to the GFC (through a pre-crisis relationship with a bank whose balance sheet is more exposed to the GFC) leads to lower productivity-enhancing investment (R&D, advertising, marketing) post-crisis. Lastly, considering 17 OECD countries, Ahn et al. (2018) observe that post-2008 investment in intangibles is lower for firms displaying higher leverage pre-crisis. They also find that monetary easing mitigates the impact of the financial crisis for high-leverage firms. This result is complementary to those obtained by the cleansing literature: monetary easing can, at the same time, keep low-productivity firms afloat and help high-leverage firms invest despite financial vulnerability.

We contribute to this literature by highlighting the heterogeneity of TFP reaction to credit constraints depending on the country. The existing literature mostly investigates either one country or a panel of countries, without comparing firms of different countries in a systematic way. A recent exception is Levine and Warusawitharana (2020) who perform dynamic panel regressions separately for Spain, France and Italy. They find that, in the three countries, more financial frictions (measured through industry-adjusted firm-level leverage) raise the (positive) sensitivity of TFP growth to debt growth. When measuring financial frictions at the country level through 10-year sovereign bonds spreads, though, this relationship disappears for Spain. Furthermore, Di Mauro et al. (2020) find a positive elasticity of credit growth to TFP growth in Italy, which they interpret as the result of liquidity constraints, but not in Spain or France. Here we do not investigate the link between credit growth and TFP growth, but rather between financial fragility, credit tightness and TFP variations. Lagged firm-level leverage is considered to be a fragility rather than an input for TFP. We follow Altomonte et al. (2018) to address endogeneity issues. Our dependent variable is the level of TFP which we regress on firm-level variables and a range of fixed effects, which allows us to identify the variables that affect TFP deviations from firm-specific and sector-time specific averages.[5]

3 Data

Our firm-level data are extracted from the Amadeus-Orbis database (through Bureau van Dijk). We use a panel of manufacturing firms in France, Italy and Spain from 2000 to 2017. These three countries are generally regarded as having high rates of firm coverage when compared to European business registers (Kalemli-Özcan et al., 2015). In this section, we first describe how firm-level TFP is recovered from Amadeus, before presenting our measures of credit constraints.

3.1 Measurement of TFP

Firm-level TFP is recovered from an estimated firm-level production function. We use the standard estimation routine of Levinsohn and Petrin (2003) which builds on the framework of Olley and Pakes (1996).[6]

We take variations in intermediate input use as a proxy for unobserved productivity shocks in the estimation of the production function.[7] Assuming a Cobb-Douglas production function in log terms, we estimate

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + s_t\left(k_{it}, m_{it}\right) + u_{it} \tag{1}$$

where y_{it} is firm i's value added in period t, k_{it} is capital, l_{it} is labor, m_{it} is intermediate inputs and $s_t\left(k_{it}, m_{it}\right)$ proxies ω_{it}, the unobserved productivity shock.[8] Labor l_{it} is assumed to be freely and costlessly adjustable, whereas capital k_{it} is assumed to be determined by past capital k_{it-1}

[5] Alternatively, we could have worked directly on TFP growth but, as shown by Levine and Warusawitharana (2020), TFP dynamics is complex and may lead to surprising counter-cyclical effects.

[6] A simple regression of output on input variables may be biased by transitory productivity shocks that may temporarily increase the use of one output more than the other. Such simultaneity of an unobserved productivity shock and input use would then bias the estimation of the production function and firm TFP which is derived from it. Another bias, discussed by Foster et al. (2008) and Van Beveren (2012), arises from the use of industry-level price deflators. Because firms' prices are not available in most datasets, physical quantities of inputs and outputs are usually obtained by deflating nominal variables with industry price deflators. But since individual firm prices differ from these deflators in the case of market power or quality differences, a bias is introduced in the estimation of productivity as input and/or output quantities are measured incorrectly. The measure of TFP that employs such industry price deflators must therefore be interpreted as revenue-based TFP, as discussed in Syverson (2011).

[7] Using intermediate inputs as opposed to investment, as originally proposed by Olley and Pakes (1996), has the advantage of including observations with zero investment but positive intermediate input use.

[8] Here, $s_t\left(k_{it}, m_{it}\right)$ conceptually represents $m_t^{-1}\left(k_{it}, \omega_{it}\right)$, the inverted demand function for intermediate inputs with respect to the productivity shock ω_{it}. Because its functional form is unknown, it is flexibly approximated as a third order polynomial of k_{it} and m_{it} in the estimation.

and the firm's decision to invest in period $t-1$. We relate these variables to the information contained in Amadeus data by using the book value of total assets, both current and fixed, for k_{it-1}, the number of employees for l_{it}, and materials for m_{it}. To proxy value added y_{it}, we use sales less the cost of materials and employees. Following Foster et al. (2008), we do not deflate the nominal variables with sector-level prices since these price effects are ultimately wiped out by the sector-time fixed effects.

Following Kalemli-Özcan et al. (2015), we drop all observations of a firm if total assets, sales, tangible fixed assets or employment is negative in any year or employment exceeds 2,000,000. We also drop the firm-year observations for which total assets, revenue or sales are missing. However, the most frequent missing information is employment. Like Altomonte et al. (2018), we only exclude firms for which employment is missing more than three consecutive years. We then impute the missing employment data with the predicted values of a regression of the number of employees at the firm level on labor cost, sales and year dummies, separately for each industry.[9] We have checked that the distribution of firms in year t in terms of TFP is not different whether their TFP in $t+1$ relies on imputation or not. Hence, our implicit assumption that imputed firms have similar unit wages and labor productivity as the non-imputed ones is validated in our data. There are exceptions in some years for Italy, where non-imputed firms tend to display higher and more dispersed TFP than imputed ones. However our methodology is more robust than a mere interpolation of employment at the firm level that would smooth out the impact of crises by imputing employment values that appear more stable than they are in reality.

In a second step, after the estimation of the production function, firm-level TFP $\widehat{\omega}_{it}$ is recovered as follows:

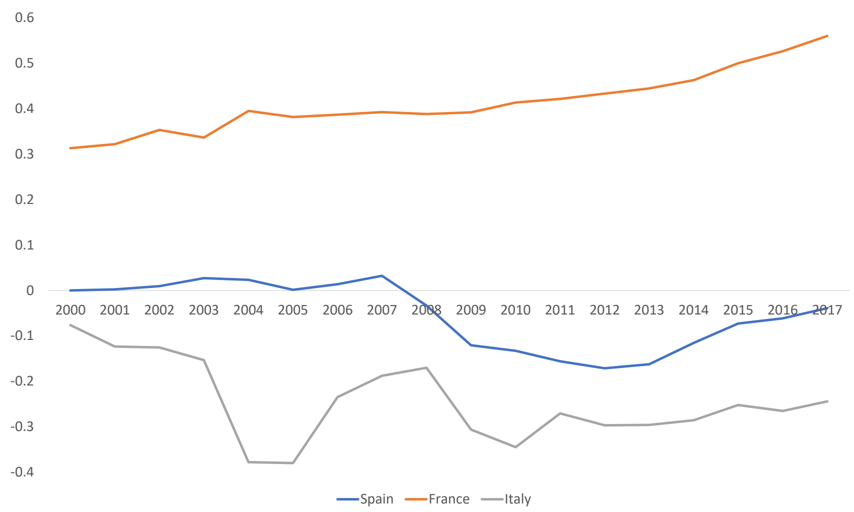
$$\widehat{\omega}_{it} = y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta_k} k_{it} \tag{2}$$

We end up with a sample of around 60,000 firms per country-year on average in Spain, 80,000 in Italy and 40,000 in France, over 2000-2017.[10] Figure 3 shows the unweighted average of TFP across firms in the three countries after controlling for different sector distributions across countries. More specifically, we regress the log of firm-level TFP on sector fixed effects and on country-time fixed effects, and we plot the latter. On average, TFP is higher and growing in France whereas it is rather flat in the two other countries, and declining after the GFC.

[9] We do not use negative predictions or predictions above the 99.5th quantile of predicted values.

[10] Unfortunately, this number is not constant over time especially in Italy and in France.

Figure 3: Evolution of TFP in each of the three countries



Source: Authors' calculations based on Orbis.
Note: The graph shows α_{ct} estimated from the following regression: $TFP_{isct} = \alpha_{ct} + \beta_s + u_{isct}$ where TFP_{isct} is the logarithm of TFP in firm i, sector s, country c, year t.

3.2 Credit conditions

Credit conditions may be measured at the level of the firm, the sector or the country. Here we use country-level measures because they are more likely to be exogenous to TFP than firm or even sector-specific constraints.

Country-specific credit conditions could be interacted with an external (US) measure of dependence on external finance (see e.g. Manova, 2013). However, the dependence on external finance may differ widely across firms of a given sector, e.g. depending on their size or business model. Hence, we rather interact country-specific credit conditions with firm characteristics such as leverage, cash-flows or tangible assets. We address the reverse-causality issue by measuring cash-flows and leverage as deviations within size bins, lagging these measures by one or two years and controlling for a set of fixed effects. We also perform robustness checks with longer lags for cash-flows and leverage, and with sector-level measures of reliance on external finance.

Three measures of credit conditions at the country level are successively considered. The first one is an index of credit tightness based on the ECB's Business Lending Survey. This quarterly survey asks senior lending officers in 150 banks in all Eurozone countries for their opinion on past changes in lending standards as well as their outlook into the future. The headline index, named "diffusion index", is constructed from a question about changes in the banks' overall credit conditions over the past three months. The index is equal to the difference between the share of banks that indicate that lending conditions over the past three months have tightened and the share of banks that indicate that credit conditions have eased, weighted by the intensity of their responses. We sum up over the quarters of a year and transform the resulting yearly changes in credit conditions into levels by setting the level of credit tightness (BLS index hereafter) to 1 in 2007 in all three countries and adding yearly changes to this base.[11]

For our second measure of credit conditions, we rely on the spreads on government bonds, taken from the IMF's International Financial Statistics. As noted already by Mody (2009), there is a close relationship in the Euro area between perceived sovereign risk and the vulnerability of banks – the so called bank-sovereign doom loop. In the short run, sovereign risk is exogenous to firm-level TFP. The fact that sovereign spreads may not be exogenous to the ability of banks to extend new credit does not preclude using them as a proxy for credit constraints.[12] The variable refers to the average yearly yield of government and/or public sector bonds with at least two years of maturity differenced from the average yearly yield on German public sector obligations.

Finally, we use a novel measure of distress in a country's financial system proposed by Romer and Romer (2017).[13] This measure is constructed from the narrative appraisals of a country's financial conditions contained in the semi-annual *OECD World Economic Outlook*, published for all OECD member countries since 1967. Romer and Romer (2017) classify the descriptions of disruptions to the cost of credit intermediation into five categories (credit disruption, minor crisis, moderate crisis, major crisis, extreme crisis) with three graduations each (minus, regular, plus). Accordingly, they assign a number between one and 15 to the descriptions of each country in each *OECD World Economic Outlook*. They do so in a systematic manner that pays attention both to the wording and to the prominence of the discussions of financial disruptions in the OECD's overall account of a country's economic situation. The resulting measure has the advantage of being holistic, as opposed to a narrowly defined statistical indicator, but is susceptible to biases in the OECD's description of financial distress and Romer & Romer's appraisal thereof.

Figures 4, 5 and 6 and compare our three measures of credit constraints respectively for Spain, Italy and France. We have checked that, consistent with the "doom loop", sovereign

[11]Setting the index at the same level for the three countries in 2007 is benign since all our estimations include fixed effects.

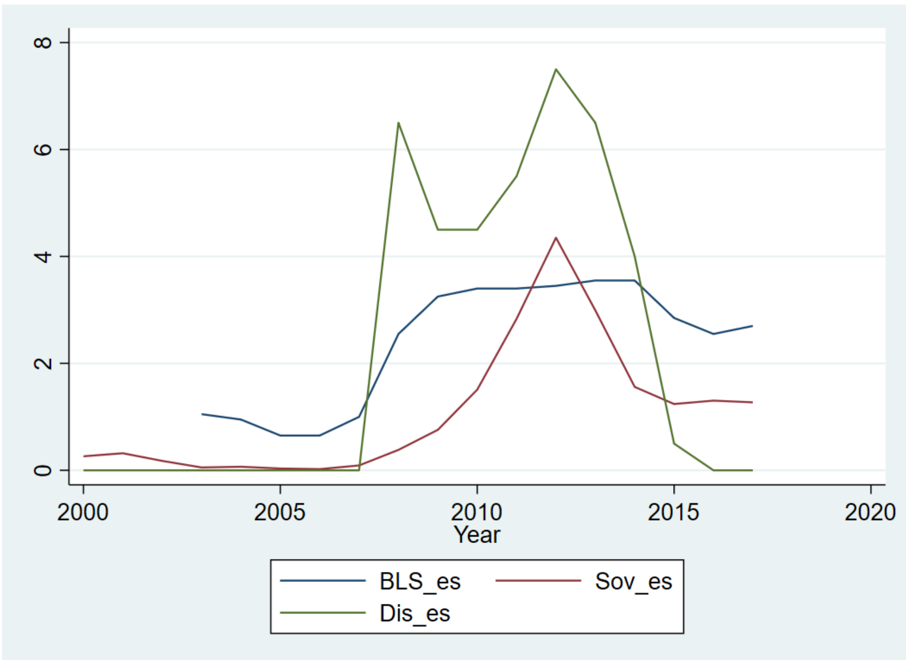
[12]Since government bonds represent the benchmark above which all private debts are rated, an increase in sovereign spreads will also raise the interest rate on corporate borrowing.

[13]The database was later updated by the authors up to 2017Q2.

spreads are closely correlated with an unweighted average of bank CDS spreads calculated over two banks in Spain, four in France and two in Italy, for the period 2004 through 2017. Since sovereign spreads are more reliable and available over a longer period, we do not use bank CDS spreads in our estimations.

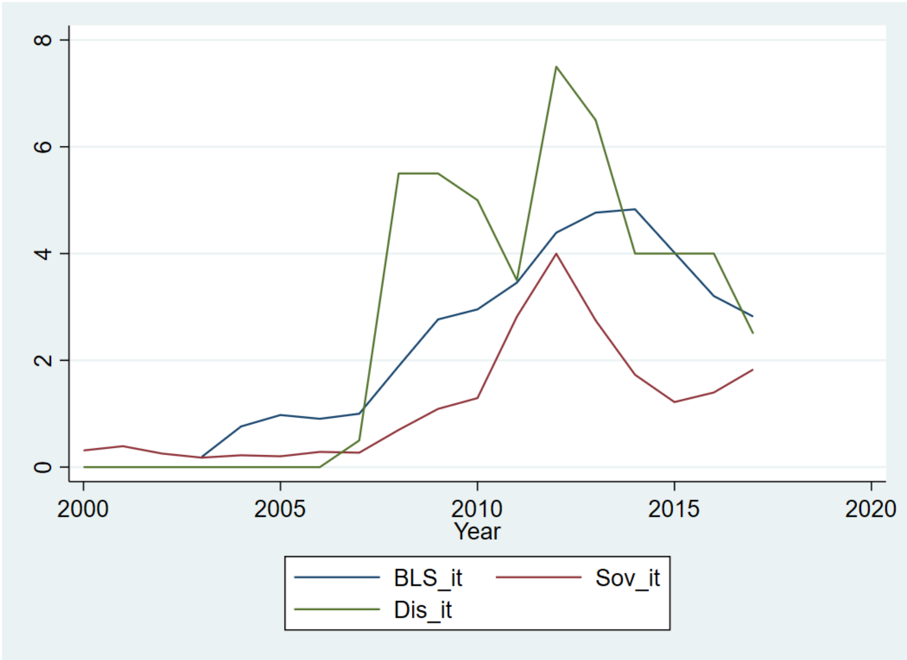
In all three countries, the sovereign spread is single peaked in 2012 whereas financial distress is double peaked (2008-09 and 2011-13). In France, though, the second peak is less marked than in the other two countries. The different scale also reveals less credit tightening in France over the period. As for the BLS index, it rises in 2008 and reaches a plateau around 2009 in Spain and France, whereas it peaks in 2014 in Italy. On the whole, the three measures of credit conditions seem to convey somewhat different information. In particular, the BLS index is measured closest to firms, the Financial Distress index offers the most holistic appreciation of stress in the financial system and the sovereign spreads react most to sovereign default risk during the Euro area crisis.

Figure 4: Credit conditions in Spain



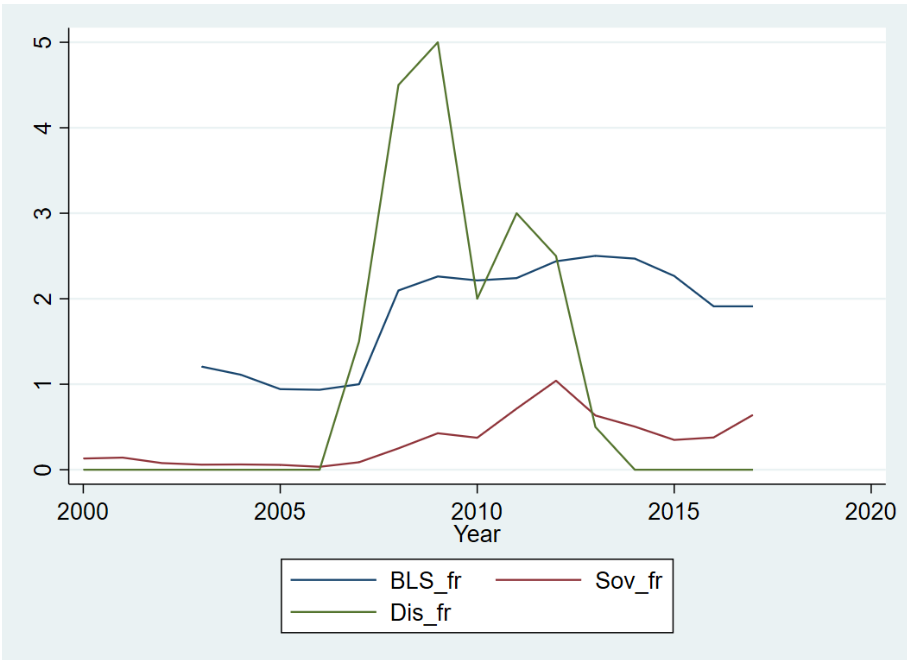
Notes: Sovereign spreads (Sov) are in percentage points; the BLS index is set to 1 in 2007; financial distress (Dis) ranges from 0 to 15.
Source: authors.

Figure 5: Credit conditions in Italy



Notes: Sovereign spreads (Sov) are in percentage points; the BLS index is set to 1 in 2007; financial distress (Dis) ranges from 0 to 15.
Source: authors.

Figure 6: Credit conditions in France



Notes: Sovereign spreads (Sov) are in percentage points; the BLS index is set to 1 in 2007; financial distress (Dis) ranges from 0 to 15.
Source: authors.

3.3 Other control variables

Firm-level controls are taken from Amadeus-Orbis. We follow Kalemli-Özcan et al. (2018) in controlling for sales, cash flows and leverage.[14] Contemporaneous sales are introduced here in log to filter log-TFP for the firm-specific firm-specific growth trend and for TFP pro-cyclicality at the firm level (since capital and labor cannot be perfectly adjusted in the short run). We then introduce lagged leverage as a measure of financial fragility. Leverage is defined as the ratio between debts (both long and short-term) and total assets.

The recent literature on resource allocation highlights the fact that lending could disproportionately flow to firms that have more collateral, which are not necessary those with higher potential in terms of TFP. In fact, Altomonte et al. (2020) find a positive correlation between fixed costs expenditures and leverage in France, suggesting "routine access to external capital" (p. 3). Such long-lasting inequality in access to funds is partly captured by firm fixed effects. However, the problem arises again when financial fragility needs to be interacted with a measure of financial frictions. Levine and Warusawitharana (2020) address the problem by adjusting their measure of leverage for the industry average. Since leverage may vary in a systematic way not only depending on the sector, but also on the country and on the size of the firm, Altomonte et al. (2018) rather propose to adjust each firm's financial characteristics (in their case, tangible assets) for the "frontier" in its country-sector-size specific "bin".[15] We follow their methodology here (see *infra*).

A drawback of the data used here is the presence of a large number of missing values for fixed assets: including this control in the regressions reduces the sample size by around 20 percent, from 2 million observations to only 1.6 million. More worryingly, the number of observations is very low from 2005 to 2008. Therefore, we decided to control for lagged firm-level collateral (the ratio of fixed to total assets) only in our robustness checks.

Lian and Ma (2019) show that, for US non-financial firms, 80% of debt is cash-flow based rather than asset-based. Hence, cash-flows may capture the ability of a firm to finance its investment either directly (using the cash-flows themselves) or as a way of getting loans. Furthermore, Canepa and Stoneman (2005) and Anzoategui et al. (2019) find evidence of a relationship between cash-flows and technology adoption. Therefore, we control for the lagged ratio between

[14] Preliminary estimations did not provide any evidence of a significant impact of firm-level interest payments on TFP. As for firm size, it is catched by the firm fixed effects in the cross-sample dimension and by firm-level sales in the within dimension.

[15] Size is measured by deciles of yearly sales.

cash-flows and total assets – both variables being widely available in Orbis.[16]

Following Altomonte et al. (2018), our three firm-level variables - leverage, cash-flows and collateral - are measured relative to their respective country-sector-size "frontiers". More specifically, for each variable, we proceed as follows:

- The sample is split into sector-country sc sub-samples;
- Each sub-sample is divided into 10 deciles d depending on firm size (based on their turnover), pooling all observations for all years in each sector-country sub-sample;
- Within each size decile d, the average of the variable under scrutiny (leverage, cash-flows or collateral) is calculated for the top-5% of this variable, which is called the "frontier" f_{dsct};
- The distance of each firm's variable of the decile, x_{isct}, to the decile-specific frontier f_{dsct} is calculated as follows: $dist_{isct} = f_{dsct} - x_{isct}$;
- Finally, our transformed variable z_{isct} is the opposite of $dist_{isct}$ so as to increase when the underlying variable x_{isct} increases: $z_{isct} = -dist_{isct}$.

The three transformed variables z_{isct} vary from -1 (lowest level in the corresponding country-sector-size "bin") to 0 (when the firm is among the top-5% highest in the bin).[17] In other words, a higher value points to *smaller* distance to the frontier. In this way, the coefficients on the normalized variables can be interpreted as if they were obtained with the initial variables. Together with sector-time fixed effects, we fully control for variations in leverage, cash-flows or collateral in average for a given sector over time. Since all variables are calculated relative to a decile of firm size, we also control for smaller firms generally displaying lower leverage, collateral and cash-flows.

In Appendix A, we report the results from the following, preliminary estimation:

$$TFP_{isct} = \beta_0 Sales_{isct} + \beta_1 X_{isct} + FE_i + FE_{st} + u_{isct} \tag{3}$$

where TFP_{isct} is the log-TFP of firm i in sector s, country c at time t, $Sales_{isct}$ is the logarithm of the sales of the same firm in the same year, and X_{isct} is the vector of lagged ratios

[16]We also carried out regressions while controlling for the country-level stock price index as a proxy for the ability of the firms to issue new equity: CAC40 for France, FTSEMIB for Italy and IBEX35 for Spain, each deflated with the respective GDP deflators from Eurostat. This variable appeared non-significant, hence it is dropped in the following.

[17]Due to some outliers, we had to normalize the cash-flow variable to fit in this range.

of cash-flows $Cash_{isct-1}$ and of leverage Lev_{isct-p} (with $p = 1, 2$). FE_i and FE_{st} are firm and sector-time fixed effects,[18] and the error terms are clustered at the sector level.[19] We compare the effect of the original variables (indexed by *orig*) to that of the transformed variables used in the remainder of the paper.

As expected, TFP is found pro-cyclical: when firm-level sales increase relative to the sector-time corresponding grouping, TFP increases for sake of economies of scale or higher utilization rate of production capacity. Likewise, lagged cash flows affect TFP positively, and the coefficient on the transformed variable is more significant than that on the original one.[20]

As for leverage, it has negative, significant impact on TFP whether it is lagged by one or two years, and whether the variable is transformed or not. Because leverage is measured at end-year, in the following we prefer to lag it by two years,[21] whereas cash-flows are lagged by only one year.[22] Conversely, we do not lag sales because the role of this variable in our estimation is essentially to filter firm-level TFP from the firm-level business cycle. Accordingly, we refrain from having any causal interpretation for this variable.

4 The impact of leverage on TFP after the GFC

Following the existing literature, we first study the impact of the GFC through the use of a dummy variable: we estimate again Equation (3) but now we interact each covariate with a post-2008 dummy:

$$TFP_{isct} = \beta_0 Sales_{isct} + \beta_1 X_{isct} + \beta_2 Post2008 \times X_{isct} + FE_i + FE_{st} + u_{isct} \quad (4)$$

where $Post2008$ is a dummy variable equal to 1 starting in 2008. The presence of sector-time fixed effects accounts for the shock of the crisis itself which may have affected the different sectors with varying intensities. In turn, the interacted variables intend to capture how different characteristics at the firm level affect the way TFP reacts to the GFC. The possible endogeneity of leverage or cash-flows with respect to TFP across firms is controlled for through the firm fixed

[18] We use the same set of fixed effects as in Kalemli-Özcan et al. (2018) and Duval et al. (2020).

[19] We cluster at sector level because our "treatment" variable (leverage) is unlikely to be randomly assigned across sectors: as demonstrated by Rajan and Zingales (1998), some sectors are more dependent on external finance than others. On the choice of clustering, see Cameron and Miller (2015) and Abadie (2017).

[20] The coefficients themselves cannot be compared as the normalization changes the scale of the cash-flow variable.

[21] Leverage at end of year $t - 2$ will affect investment in year $t - 1$, hence TFP in year t.

[22] Consistently, we will also lag collateral by also two years in the robustness check.

effects and through the transformations of both variables in relation to each sector-country-size bin. Like in the preliminary estimation, the residuals are clustered at sector level.

We first estimate Equation (4) for the whole panel of our three countries. In a second step, we drop the country dimension of the panel and estimate Equation (4) for each country separately. We also study the impact of the euro area crisis by alternatively using a Post-2011 dummy instead of a Post-2008 one.

The results for the whole panel are presented in Table 1. Sales and non-interacted cash-flows have a positive, significant impact on TFP across all specifications. As for leverage, it has a negative impact on TFP over the whole period, but this effect drops when the 2008 dummy interaction is introduced in Column (2). In fact, more leveraged firms do not seem to suffer more after the GFC, but they do see their TFP lowered after 2011 (last column). Hence, this first exercise does not confirm that more "vulnerable" firms (e.g. firms with higher leverage) were more negatively affected by the GFC. They were rather hurt by the euro area crisis.

Table 1: Impact of the Global financial crisis on TFP: whole sample

	(1)	(2)	(3)	(4)
Sales	0.458***	0.458***	0.458***	0.458***
	(0.0103)	(0.0104)	(0.0103)	(0.0103)
L.Cash	0.231***	0.200***	0.231***	0.193***
	(0.0193)	(0.0266)	(0.0193)	(0.0259)
L2.Lev	-0.0193***	-0.0107	-0.0193***	-0.0104
	(0.00486)	(0.00946)	(0.00486)	(0.00615)
Post2008# L.Cash		0.0489		
		(0.0338)		
Post2008#L2.Lev		-0.0124		
		(0.0109)		
Post2011#L.Cash				0.0919*
				(0.0482)
Post2011#L2.Lev				-0.0193***
				(0.00639)
Observations	2,030,321	2,030,321	2,030,321	2,030,321
R-squared	0.853	0.853	0.853	0.853
Sector-year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the sector level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1 does not account for the fact that the firms in the three European countries faced quite different credit environment during and after the GFC, as illustrated by Figure 2 *supra*. These countries also differ from an institutional point of view. For instance, the OECD synthetic indicator of employment protection for 2008 was 3.15 in Italy in 2008, against 2.73 in France and 2.76 in Spain.[23] If firms cannot adjust their labor force during a crisis, this mechanically

[23] Version 2 of the index, available from 1998 to 2013.

weighs negatively on productivity. The financial sectors are also different in the three countries. For instance, the European Banking Authority estimated the aggregate ratio of non-performing loans to be of 17% in Italy in March 2016, against 6% in Spain and 4% in France.[24] Hence, banks may be more reluctant to lend in Italy than in the other two countries. Other differences include the structure of the banking sector, bankruptcy laws, foreclosure regulations, etc.

Therefore, we now estimate Equation (4) for each country separately, with firm and sector-year fixed effects, i.e. controlling for all time-varying factors in the country-sector dimension. The results are reported in Table 2 (two columns per country). In all three countries, TFP is positively correlated to sales. The elasticity of TFP to sales is higher in Italy than in the two other countries, suggesting more pro-cyclicality in Italy.

Table 2: Impact of the GFC: country-by-country results

	France		Spain		Italy	
	(1)	(2)	(3)	(4)	(5)	(6)
Sales	0.402***	0.402***	0.434***	0.434***	0.483***	0.483***
	(0.0224)	(0.0224)	(0.0133)	(0.0132)	(0.0127)	(0.0127)
L.Cash	0.00370	0.0182	0.376***	0.360***	0.0777	0.125*
	(0.0330)	(0.0299)	(0.0432)	(0.0439)	(0.0571)	(0.0658)
L2.Lev	-0.0440***	-0.0303***	-0.0531***	-0.0528***	0.0721***	0.0105
	(0.0125)	(0.00825)	(0.00988)	(0.00780)	(0.0113)	(0.00764)
Post2008#L.Cash	0.0870**		-0.0454		0.298***	
	(0.0396)		(0.0410)		(0.0840)	
Post2008#L2.Lev	0.0455***		0.0242**		-0.127***	
	(0.0139)		(0.0114)		(0.0115)	
Post2011#L.Cash		0.101**		-0.0311		0.332**
		(0.0444)		(0.0468)		(0.132)
Post2011#L2.Lev		0.0367***		0.0334***		-0.0667***
		(0.0104)		(0.0100)		(0.00762)
Observations	468,357	468,357	615,669	615,669	946,295	946,295
R-squared	0.882	0.882	0.807	0.807	0.826	0.826
Year*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Lagged cash-flows have a positive impact on TFP in all three countries (but only after the two crises in France). As for leverage, it affects TFP negatively in all three countries, but the reactions to the crises are contrasted: more leveraged firms suffer more from both the GFC and the euro crisis in Italy, but they suffer *less* in the other two countries. Hence, the standard result according to which weaker firms suffer more from a financial crisis is not confirmed by our results in Spain and in France, although it is in Italy.[25]

[24]Source: EBA Report on the Dynamics and Drivers of Non-Performing Exposures in the EU Banking Sector, 22 July 2016.

[25]Note that the number of observations in Italy is higher than in the other two countries, which may explain why the results on the whole sample look like those for Italy.

At this stage, though, we cannot assess whether these diverging reactions across countries are due to different credit shocks (see Figures 4, 5, 6) or to different reactions to a given credit tightening. Hence this first exercise does not really allow to measure the impact of financial crises on TFP growth. It rather highlights different behaviours of firms in the three countries after a common shock. We must contemplate a different strategy and estimate the impact of country-year credit conditions on TFP.

5 The impact of country-specific credit conditions

We now drop the crisis dummy strategy and directly study the impact of country-year credit conditions CC_{ct} on TFP by estimating the following equation:

$$TFP_{isct} = \beta_0 Sales_{isct} + \beta_1 X_{isct} + \beta_2 CC_{ct} + \beta_3 CC_{ct} \times X_{isct} + FE_i + FE_{st} + u_{isct} \qquad (5)$$

where CC_{ct} successively covers the lagged value of our three measures of credit constraints: (i) BLS index, (ii) sovereign spreads, and (iii) financial distress. The other variables are the same as before. We include firm and sector-year fixed effects, hence we are still studying firm-level deviations from their sector cells over time.[26] The residuals are again clustered at sector level.

5.1 Baseline results

The results for the whole panel pooling the three countries together are reported in Appendix B, Table B1. Sales and non-interacted cash-flows have on average a positive impact on TFP whereas financial constraints (whether represented by the BLS index, the sovereign spread or the financial distress index) have on average a negative effect. Furthermore, the positive impact of cash-flows on TFP is magnified when financial conditions tighten. This is expected, as firms have to rely on their cash-flows to directly finance their investments or convince creditors to lend. As for leverage, it generally has a negative impact on average, but mostly when interacted with financial constraints.

These results could be interpreted as clear evidence that weaker firms (more leverage, less cash flows) see their TFP decrease more after a financial crisis. As evidenced in the previous section, though, pooling the three countries together may hide significant differences across

[26] Additional country-time variables such as GDP did not appear significant in preliminary estimations, the business cycle being better accounted for at the firm level through the sales variable.

countries. Hence, we re-estimate Equation (5) for each country separately, dropping the country subscript and the non-interacted measure of credit tightness (which is redundant with respect to sector-time fixed effects).

The results are reported in Table 3 (three columns for each country). Like in the previous section, we find strong pro-cyclicality of TFP with respect to sales, especially in Italy. However, now, the impact of cash-flows is not always significant except in Spain. Leverage has a negative impact on TFP in France and in Spain, but less so when financial conditions tighten. Conversely, leverage has a positive impact on TFP in Italy when credit conditions are loose, but a negative impact when they tighten. Hence, the usual narrative according to which firms with more leverage would have been hit harder by the different credit crises only corresponds to Italy in our estimation results.

Table 3: Impact of country-specific credit constraints on TFP: country-by-country results

		France			Spain			Italy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales	0.419***	0.402***	0.402***	0.454***	0.434***	0.434***	0.503***	0.483***	0.483***
	(0.0225)	(0.0224)	(0.0225)	(0.0140)	(0.0133)	(0.0133)	(0.0125)	(0.0127)	(0.0127)
L.Cash	0.0307	0.00702	0.0420	0.411***	0.385***	0.397***	0.0585	0.144**	0.205***
	(0.0596)	(0.0315)	(0.0299)	(0.0507)	(0.0486)	(0.0487)	(0.0840)	(0.0546)	(0.0448)
L2.Lev	-0.0643***	-0.0373***	-0.0318***	-0.0535***	-0.0480***	-0.0422***	0.0550***	0.0158**	0.0240***
	(0.0124)	(0.0104)	(0.00698)	(0.0167)	(0.00700)	(0.00757)	(0.0104)	(0.00748)	(0.00778)
L.Cash#L.BLS	0.00755			-0.0431**			0.0850**		
	(0.0323)			(0.0159)			(0.0338)		
L2.Lev#L.BLS	0.0364***			0.0136**			-0.0262***		
	(0.00676)			(0.00554)			(0.00295)		
L.Cash#L.Sov		0.155**			-0.0329**			0.109***	
		(0.0728)			(0.0155)			(0.0368)	
L2.Lev#L.Sov		0.0664***			0.00871***			-0.0297***	
		(0.0190)			(0.00278)			(0.00315)	
L.Cash#L.Dis			0.00726			-0.0192***			0.0245**
			(0.00739)			(0.00606)			(0.00878)
L2.Lev#L.Dis			0.00950***			0.00165			-0.0137***
			(0.00142)			(0.00167)			(0.00134)
Observations	394,452	468,357	468,357	533,274	615,669	615,669	882,647	946,295	946,295
R-squared	0.892	0.882	0.882	0.818	0.807	0.807	0.833	0.826	0.826
Year*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

5.2 The Italian case

In this section, we dig into the specificity of Italy with respect to the other two countries.

As already mentioned, the OECD considers employment regulations to be more restrictive in Italy than in Spain or France, at least during the period under review. To the extent that these regulations constitute a stronger impediment to labor reallocation for firms with a smaller internal labor market, they could weigh more on TFP growth in small firms than in larger ones. However, smaller firms generally benefit from special provisions. In Italy, firms with less than 15 employees benefit from many special legal and tax treatments.[27]

Here we estimate Equation (5) separately for Italian firms below 15 employees or with 15 employees or more.[28] The results are reported in Table 4. For all three measures of credit constraints, we find that only small firms suffer from high leverage when credit conditions tighten For two measures of credit constraints, having more cash-flows is also a protection for smaller firms. Hence, the negative impact of leverage during and after financial crises that is found in Italy seems to come from smaller firms: despite preferential treatment, smaller firms find it more difficult to adjust their production capacity. These results are consistent with Calligaris et al. (2016) and Pellegrino and Zingales (2019) who note that Italian banks have long been lending to firms with low productivity prospects - a feature that has created large volumes of non-performing loans during the crisis. Banks preferred to continue to lend to these "zombie firms" during the crisis, which in our data has a negative impact on TFP (see Schivardi et al., 2017). Our results are also consistent with Maranesi and Pierri (2019) who find that small firms in more leveraged sectors see their TFP more affected by a negative shock on credit supply. However their firm-bank dataset does not allow them to compare TFP growth across countries.

Indeed, it could be argued that the results presented in Table 4 are not specific to Italy: in all countries, leverage is more detrimental to smaller firms during a crisis, not least because larger firms have easier access to financial markets. Hence, we re-estimate Equation (5) for small firms in all three countries, using the standard 10 employees threshold. The results are displayed in Appendix B, Table B2. We find a negative impact of leverage interacted with financial constraints only in Italy. In Spain, this interaction has no significant effect where as in France, the effect is positive.

Another possible explanation for the vulnerability of leveraged firms in Italy is the short

[27] The most significant special rule concerns the non application of article 18 of workers' statute that constrains dismissals especially before the 2012 labor reform.

[28] Alternatively, we use the standard threshold of 10 employees, see *infra*.

Table 4: Impact of credit constraints on TFP in Italy: large versus small firms

	Large firms (≥ 15)			Small firms (< 15)		
	(1)	(2)	(3)	(4)	(5)	(6)
Sales	0.531***	0.509***	0.509***	0.566***	0.557***	0.557***
	(0.0198)	(0.0193)	(0.0193)	(0.0111)	(0.0111)	(0.0111)
L.Cash	0.273***	0.201***	0.223***	0.135**	0.189***	0.281***
	(0.0734)	(0.0657)	(0.0648)	(0.0634)	(0.0507)	(0.0763)
L2.Lev	-0.0385***	-0.0440***	-0.0399***	0.0170	0.00717	0.00612
	(0.00994)	(0.00812)	(0.00882)	(0.0122)	(0.00976)	(0.0102)
L.Cash#L.BLS	-0.0434**			0.0636***		
	(0.0163)			(0.0213)		
L2.Lev#L.BLS	6.39e-05			-0.0146***		
	(0.00254)			(0.00274)		
L.Cash#L.Sov		-0.0193			0.0905***	
		(0.0206)			(0.0226)	
L2.Lev#L.Sov		-0.00369			-0.0238***	
		(0.00312)			(0.00327)	
L.Cash#L.Dis			-0.0151*			0.00997
			(0.00744)			(0.00965)
L2.Lev#L.Dis			-0.00288			-0.00875***
			(0.00187)			(0.00158)
Observations	370,191	413,863	413,863	496,932	516,732	516,732
R-squared	0.894	0.885	0.885	0.836	0.831	0.831
Firm FE	yes	yes	yes	yes	yes	yes
Sector-time FE	yes	yes	yes	yes	yes	yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

maturity of their debt. Over the whole period, the median share of short-term debt (with maturity of up to one year) in total debt is 70 percent in Italy, against 52 percent in France and 17 percent in Spain. Hence, there is higher rollover risk for Italian firms, which makes them more vulnerable to credit tightening. In order to test this possibility, we estimate Equation (5) separately for firms where short-term debt represents more than 50 percent of total debt and for those where it represents less than 50 percent. Table 5 validates this interpretation.

Then, it could be asked whether French or Spanish firms with more short-term debt would behave like the Italian ones. This possibility is explored in Table B3 in Appendix B. French and Spanish firms with more short-term debt do not behave like Italian firms. Hence, short-term debt seems to make firms more vulnerable only in Italy. According to Berton et al. (2018), 90% of firms in Veneto have less than ten employees, and they are much more indebted than larger firms. Consistently, in our results, it is the combination of size and leverage that seems to drive the peculiar behavior of TFP in Italy.

Storz et al. (2017) use information from Amadeus/Orbis for 400,000 SMEs in seven countries (France, Germany, Greece, Ireland, Portugal, Spain and Slovenia) matched with 900 banks over the period 2010-14. They have information on the stress of banks and define zombie firms as businesses with negative returns and investments. They show that an increase in bank stress translates into higher lending to zombie firms so defined in the five countries of the "periphery", whereas this is neither observed in France nor Germany. Such "zombie bias" is confirmed in Andrews and Petroulakis (2009) who do the same type of exercise on 11 European countries firms matched with 30,000 banks. It is argued that zombie firms crowd-out healthy firms from financing. Our results are consistent with both papers in the case of Italy.

Table 5: Impact of credit constraints on TFP in Italy: short-term debt

	Short-term debt <50%			Short-term debt >50%		
	(1)	(2)	(3)	(4)	(5)	(6)
Sales	0.566***	0.559***	0.559***	0.497***	0.476***	0.476***
	(0.0130)	(0.0129)	(0.0129)	(0.0133)	(0.0138)	(0.0138)
L.Cash	0.111	0.104	0.179**	0.0402	0.131**	0.191***
	(0.0953)	(0.0699)	(0.0642)	(0.0834)	(0.0545)	(0.0450)
L2.Lev	0.0181	0.0450***	0.0646***	0.0677***	0.0187**	0.0231***
	(0.0132)	(0.0103)	(0.00901)	(0.0122)	(0.00795)	(0.00801)
L.Cash#L.BLS	0.0312			0.0905**		
	(0.0299)			(0.0338)		
L2.Lev#L.BLS	0.00801			-0.0316***		
	(0.00483)			(0.00356)		
L.Cash#L.Sov		0.0667*			0.117***	
		(0.0357)			(0.0368)	
L2.Lev#L.Sov		-0.00468			-0.0331***	
		(0.00474)			(0.00401)	
L.Cash#L.Dis			0.00508			0.0276***
			(0.0121)			(0.00853)
L2.Lev#L.Dis			-0.00720***			-0.0140***
			(0.00178)			(0.00148)
Observations	163,213	166,697	166,697	698,564	758,899	758,899
R-squared	0.884	0.883	0.883	0.833	0.826	0.826
Firm FE	yes	yes	yes	yes	yes	yes
Sector-time FE	yes	yes	yes	yes	yes	yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Finally, the literature has often mentioned local developments to be a key ingredient of firms financing in Italy (see e.g. Benfratello et al., 2008 or Guiso et al., 2004b). Here, we test for a geographic pattern in our results by running the estimation separately for firms located in the North and for those located in the South, as evidenced by their region of location.[29] The results are reported in Table 6. We get very similar results for the South (first three columns) as for the North (first three columns). Interestingly, the pro-cyclicality of TFP with respect to sales is more pronounced in the South than in the North. But leveraged firms and firms with more cash-flows perform similarly when credit conditions tighten.

In this table as in Table 5, we observe that the non-interacted coefficient on leverage is

[29]We allocate the zip codes based on ISTAT definitions of "North" and "South".

positive and often significant. This may be explained by agency problems (se e.g. Berger et al., 2006). In presence of outside ownership, managers may make decisions that do not maximize the efficiency and value of the firm; leverage reduces the incentive for managers to pursue their own objectives through the threat of liquidation (Jensen and Meckling, 1976; Grossman and Hart, 1982; Pellegrino and Zingales, 2019).

Table 6: Impact of credit constraints on TFP in Italy: South versus North

	South			North		
	(1)	(2)	(3)	(4)	(5)	(6)
Sales	0.573***	0.559***	0.559***	0.485***	0.465***	0.465***
	(0.0111)	(0.0120)	(0.0120)	(0.0152)	(0.0155)	(0.0154)
L.Cash	-0.0704	0.0211	0.113	0.0834	0.168***	0.222***
	(0.101)	(0.0746)	(0.0884)	(0.0866)	(0.0552)	(0.0442)
L2.Lev	0.0423**	0.0180	0.0198	0.0518***	0.0130	0.0214**
	(0.0196)	(0.0142)	(0.0154)	(0.0115)	(0.00792)	(0.00882)
L.Cash#L.BLS	0.116***			0.0793**		
	(0.0327)			(0.0347)		
L2.Lev#L.BLS	-0.0292***			-0.0242***		
	(0.00655)			(0.00315)		
L.Cash#L.Sov		0.166***			0.0982**	
		(0.0351)			(0.0378)	
L2.Lev#L.Sov		-0.0437***			-0.0263***	
		(0.00914)			(0.00308)	
L.Cash#L.Dis			0.0381***			0.0221**
			(0.0108)			(0.00921)
L2.Lev#L.Dis			-0.0171***			-0.0125***
			(0.00355)			(0.00150)
Observations	133,508	140,646	140,646	749,137	805,647	805,647
R-squared	0.792	0.785	0.785	0.828	0.820	0.820
Firm FE	yes	yes	yes	yes	yes	yes
Sector-time FE	yes	yes	yes	yes	yes	yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

6 Robustness checks

6.1 Selection bias

Our first robustness check concerns a possible selection bias, if the firms that drop from (or join) the sample over time are systematically different from those that stay. In order to address this concern, we re-estimate Equation (5) on firms that are present at least 10 years in our sample period.[30] The results are reported in Appendix C, Table C1. They are similar to our main results reported in Table 3. Hence, our results cannot be explained by a selection bias.

[30] Few firms are present over the whole period of 17 years.

6.2 Collateral

Second, our estimations may be biased by the fact that, within a bin of sector-country-size, those firms with more leverage have accumulated collateral which facilitates access to new credit. We have not controlled for collateral in our baseline specification due to a proliferation of missing values in some years. Still, within the sub-sample of firms with data on collateral, we have a 23 percent correlation between our leverage and collateral variables. Hence, we re-run the same estimation while controlling for collateral. The results are reported in Appendix C, Table C2. Collateral has a negative impact on TFP in France and in Italy, but not in Spain. More importantly, its interaction with credit condition has no significant impact in these two countries, while it has a significant impact in Italy but with a different sign across the measures of credit constraints. All in all, the results for leverage are left unchanged. Hence, we cannot explain our results by the interplay between leverage and collateral.

6.3 Reverse causality

Our baseline specification controls for reverse causality (from TFP to leverage) by lagging leverage, controlling for firm and for sector-time fixed effects and by measuring leverage (and cash flows) as individual deviations within deciles of firm size. However, we cannot fully exclude that, within size bins and sector-time cells, individual leverage may be affected by TFP growth (if firms with good TFP prospects have better access to credit). Our third robustness test consists in lagging cash-flows and leverage by three and four years, successively. As the number of observations drops fast when longer lags are introduced, a trade-off needs to be made between the precision of the estimation and the correction of possible reverse causality.

The results are reported in Appendix C, Tables C3 and C4. They are similar to those obtained in Table 3. Only in one case (four-year lag, credit tightness proxied by BLS index) is the interacted coefficient between leverage and credit tightness found insignificant (although still negative) in Italy.

6.4 External finance

Finally, our methodology, which expresses cash-flows, leverage and collateral in relative terms with respect to each firm's country-sector-size "bin", controls for possibility that some categories of firms, say large firms in sectors that already have high leverage, may have better access to funding than smaller firms in other sectors during financial crises: we only measure whether, within a category of country-sector-size, firms with more cash-flows or leverage perform differently.

Since Rajan and Zingales (1998), though, it has been argued that industries differ widely in terms of their reliance on external finance, which in turn may trigger different vulnerability with respect to a financial crisis. Consistently, Rajan and Zingales (1998) compute a sector-specific index of reliance on external finance based on capital expenditure not financed using cash flows from operations, with US Compustat data. They subsequently show that financial deepening allows more externally dependent sectors to grow relatively faster over the long term. However, Kroszner et al. (2007) show that sectors that are highly dependent on external finance tend to suffer greater contraction of value added during a financial crisis in countries with deeper financial systems, compared to countries with less developed financial sectors.

We therefore introduce the updated index of reliance on external finance resources taken from Eichengreen et al. (2011) based on US firms, hence fully exogenous for our three countries. We convert the ISIC2 into the Nace 2-digit classification in Orbis and use the indicator for year 2000 (labelled EF), which we interact with our three measure of credit tightness, successively.[31]

The results are reported in Appendix C, Table C5. We first interact EF with cash-flows and with leverage. The coefficients are found insignificant, except in Italy where more leverage has positive impact on TFP in those sectors that are more reliant on external finance. The next lines interact EF with both cash-flows (or leverage) and credit conditions. These triple interactions are never significant. However, the simple interaction between leverage and credit condition stays negative and highly significant across the three measures of credit conditions in Italy. Hence, our specific results obtained for Italy cannot be explained by a differentiated impact of reliance on external finance.

7 Conclusion

The productivity slowdown observed in advanced economies since the mid 1990s remains to be fully understood. On top of explanations related to the diffusion of innovation, market structures, or even mis-management, a key question is whether the GFC and the Eurozone crisis may have contributed to this slowdown. To shed light on this macroeconomic issue, information at the microeconomic level is needed in order to measure firm-level productivity and identify

[31] We have normalized EF so that it ranges from 0 (lowest dependence on external finance) to 1 (highest dependence).

extensive and intensive margins of TFP growth.

We firstly show that using an identification strategy relying on differences between pre- and post- crisis year hardly fits the narrative of the crises in Europe. There has indeed been two subsequent shocks, and the exact timing of the second, as well as its intensity, differ across European countries. We also show that idiosyncratic differences in national financial systems and regulatory environments jeopardize any approach based on pooling data for European countries. Taking the example of France, Italy and Spain, we show that one size does not fit all: despite the completion of the single market, the single currency and the more recent introduction of the banking union, the reaction of firms to credit conditions is still very much country-specific in the Euro area.

Specifically, we show that the narrative according to which more leveraged firms have been hit harder by the different credit crises only corresponds to Italy. Within this country, only small firms and firms with short-term debts suffer from being highly leveraged when credit conditions tighten. Having more cash-flows is a protection for these small players. Hence, the negative impact of leverage during financial crises in Italy is driven by smaller firms, especially when their debts have a short maturity. Our results are consistent with the literature on the lending behavior of Italian banks: they have been lending to firms with low productivity prospects for a long time; this has led to the accumulation of large volumes of non-performing loans and to a tendency to lend to “zombie firms”. The combination of size and leverage is ultimately driving the atypical behavior of TFP in Italy, but in Italy only.

These results are robust: we have checked that they are not driven by a selection bias, the interplay between leverage and collateral, a reverse causality bias, or differences in sector-level reliance on external finance. This heterogeneity in responses to credit conditions underline the importance of completing the European banking union and developing the European capital market union for the sake of TFP growth in all parts of the Euro area.

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Appendix A: Preliminary estimation

Table A1. The impact of firm-level variables on TFP

	(1)	(2)	(3)	(4)
Sales	0.447***	0.457***	0.448***	0.458***
	(0.00971)	(0.0104)	(0.00968)	(0.0103)
L.Cash_old	0.0201**	0.0201**		
	(0.00855)	(0.00863)		
L.Lev_orig	-0.0610***			
	(0.00578)			
L2.Lev_orig		-0.0106**		
		(0.00429)		
L.Cash			0.219***	0.231***
			(0.0187)	(0.0193)
L.Lev			-0.0744***	
			(0.00664)	
L2.Lev				-0.0193***
				(0.00486)
Observations	2,362,774	2,031,423	2,360,652	2,030,321
R-squared	0.843	0.853	0.843	0.853
Firm FE	yes	yes	yes	yes
Sector-time FE	yes	yes	yes	yes

Note: Pooled sample. Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix B: Baseline specification - Additional results

Table B1. Impact of country-specific credit constraints on TFP: whole panel

	(1)	(2)	(3)	(4)	(5)	(6)
Sales	0.478***	0.479***	0.456***	0.457***	0.457***	0.457***
	(0.0104)	(0.0105)	(0.0103)	(0.0103)	(0.0104)	(0.0104)
L.Cash	0.222***	0.141***	0.231***	0.179***	0.232***	0.220***
	(0.0195)	(0.0411)	(0.0194)	(0.0229)	(0.0195)	(0.0226)
L2.Lev	0.00110	0.0527***	-0.0161***	-0.00262	-0.0170***	0.000829
	(0.00496)	(0.0156)	(0.00486)	(0.00770)	(0.00477)	(0.00881)
L.BLS	-0.000594	-0.00915**				
	(0.00338)	(0.00365)				
L.Cash#L.BLS		0.0347*				
		(0.0182)				
L2.Lev#L.BLS		-0.0214***				
		(0.00493)				
L.Sov			-0.0191***	-0.0235***		
			(0.00206)	(0.00371)		
L.Cash#L.Sov				0.0544***		
				(0.0179)		
L2.Lev#L.Sov				-0.0121***		
				(0.00353)		
L.Dis					-0.00768***	-0.0111***
					(0.000687)	(0.00148)
L.Cash#L.Dis						0.00481
						(0.00426)
L2.Lev#L.Dis						-0.00642***
						(0.00192)
Observations	1,810,373	1,810,373	2,030,321	2,030,321	2,030,321	2,030,321
R-squared	0.860	0.860	0.853	0.853	0.853	0.853
Year*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Table B2. Impact of country-specific credit constraints on TFP: firms with less than 10 employees

		France			Spain			Italy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales	0.497***	0.485***	0.485***	0.560***	0.544***	0.544***	0.592***	0.585***	0.585***
	(0.0373)	(0.0352)	(0.0352)	(0.0143)	(0.0132)	(0.0132)	(0.0103)	(0.0103)	(0.0103)
L.Cash	-0.0159	-0.0247	-0.0197	0.332***	0.395***	0.400***	0.347***	0.303***	0.364***
	(0.0792)	(0.0270)	(0.0338)	(0.0685)	(0.0563)	(0.0523)	(0.120)	(0.0936)	(0.0943)
L2.Lev	-0.0562***	-0.0157*	-0.000598	-0.0207	-0.0206***	-0.0139**	-0.0158	-0.00513	-0.00795
	(0.0116)	(0.00882)	(0.00726)	(0.0135)	(0.00561)	(0.00512)	(0.0106)	(0.00756)	(0.00881)
L.Cash#L.BLS	-0.0168			0.00122			0.00739		
	(0.0540)			(0.0319)			(0.0280)		
L2.Lev#L.BLS	0.0462***			0.00926			-0.00504		
	(0.00708)			(0.00617)			(0.00305)		
L.Cash#L.Sov		-0.00839			-0.0175			0.0397	
		(0.112)			(0.0225)			(0.0267)	
L2.Lev#L.Sov		0.0916***			0.00459			-0.0169***	
		(0.0128)			(0.00328)			(0.00328)	
L.Cash#L.Dis			-0.00404			-0.00936			-0.000280
			(0.0183)			(0.00952)			(0.0103)
L2.Lev#L.Dis			0.00671***			-0.000440			-0.00575***
			(0.00187)			(0.00200)			(0.00188)
Observations	189,076	218,922	218,922	275,040	309,671	309,671	343,997	355,020	355,020
R-squared	0.861	0.855	0.855	0.811	0.803	0.803	0.849	0.845	0.845
Year*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Table B3. Impact of country-specific credit constraints on TFP: firms short-term debt > 50% of total debt

		France			Spain			Italy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales	0.423***	0.407***	0.407***	0.471***	0.454***	0.454***	0.497***	0.476***	0.476***
	(0.0144)	(0.0154)	(0.0154)	(0.0164)	(0.0147)	(0.0148)	(0.0133)	(0.0138)	(0.0138)
L.Cash	-6.79e-05	-0.0149	0.0201	0.378***	0.305***	0.327***	0.0402	0.131**	0.191***
	(0.0679)	(0.0338)	(0.0312)	(0.0756)	(0.0516)	(0.0559)	(0.0834)	(0.0545)	(0.0450)
L2.Lev	-0.0231	-0.00270	-0.00560	-0.0936***	-0.0815***	-0.0896***	0.0677***	0.0187**	0.0231***
	(0.0230)	(0.00987)	(0.00741)	(0.0201)	(0.00992)	(0.0110)	(0.0122)	(0.00795)	(0.00801)
L.Cash#L.BLS	0.0204			-0.0670**			0.0905**		
	(0.0365)			(0.0239)			(0.0338)		
L2.Lev#L.BLS	0.00766			0.0192***			-0.0316***		
	(0.0124)			(0.00630)			(0.00356)		
L.Cash#L.Sov		0.171**			-0.0497*			0.117***	
		(0.0824)			(0.0241)			(0.0368)	
L2.Lev#L.Sov		-0.0104			0.0240***			-0.0331***	
		(0.0225)			(0.00471)			(0.00401)	
L.Cash#L.Dis			0.00807			-0.0281***			0.0276***
			(0.00875)			(0.00887)			(0.00853)
L2.Lev#L.Dis			-0.000323			0.0129***			-0.0140***
			(0.00323)			(0.00208)			(0.00148)
Observations	212,951	273,332	273,332	195,115	215,648	215,648	698,564	758,899	758,899
R-squared	0.906	0.898	0.898	0.842	0.837	0.837	0.833	0.826	0.826
Year*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C: Robustness checks

Table C1. Impact of country-specific credit constraints on TFP: firms that are at least 10 years in the sample

		France			Spain			Italy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales	0.404***	0.384***	0.384***	0.446***	0.426***	0.426***	0.491***	0.473***	0.473***
	(0.0196)	(0.0200)	(0.0201)	(0.0143)	(0.0137)	(0.0137)	(0.0127)	(0.0128)	(0.0128)
L.Cash	0.0852	0.0436	0.0796**	0.478***	0.445***	0.459***	0.0680	0.194***	0.252***
	(0.0623)	(0.0323)	(0.0327)	(0.0539)	(0.0497)	(0.0500)	(0.0931)	(0.0618)	(0.0527)
L2.Lev	-0.0701***	-0.0492***	-0.0492***	-0.0595***	-0.0529***	-0.0479***	0.0563***	0.0102	0.0217**
	(0.0107)	(0.00962)	(0.00676)	(0.0180)	(0.00766)	(0.00855)	(0.0112)	(0.00818)	(0.00835)
L.Cash#L.BLS	-0.00645			-0.0539***			0.0891**		
	(0.0334)			(0.0171)			(0.0356)		
L2.Lev#L.BLS	0.0351***			0.0156**			-0.0258***		
	(0.00583)			(0.00570)			(0.00302)		
L.Cash#L.Sov		0.139*			-0.0447**			0.0961**	
		(0.0765)			(0.0164)			(0.0372)	
L2.Lev#L.Sov		0.0662***			0.0102***			-0.0262***	
		(0.0186)			(0.00300)			(0.00338)	
L.Cash#L.Dis			0.00456			-0.0245***			0.0204**
			(0.00751)			(0.00646)			(0.00852)
L2.Lev#L.Dis			0.0136***			0.00274			-0.0133***
			(0.00174)			(0.00174)			(0.00145)
Observations	332,680	386,785	386,785	442,866	499,671	499,671	737,551	784,850	784,850
R-squared	0.889	0.879	0.879	0.810	0.800	0.800	0.828	0.822	0.822
Year*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Table C2. Impact of country-specific credit constraints on TFP: controlling for collateral

	France			Spain			Italy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales	0.442***	0.402***	0.403***	0.478***	0.440***	0.441***	0.526***	0.492***	0.492***
	(0.0225)	(0.0227)	(0.0228)	(0.0140)	(0.0133)	(0.0133)	(0.0128)	(0.0129)	(0.0129)
L.Cash	-0.0473	-0.0461	0.00143	0.326***	0.366***	0.360***	-0.0636	0.1000*	0.170***
	(0.0733)	(0.0393)	(0.0355)	(0.0600)	(0.0516)	(0.0517)	(0.107)	(0.0539)	(0.0364)
L2.Lev	-0.0238	-0.0408**	-0.0192*	-0.0251	-0.0494***	-0.0386***	0.0683***	0.00475	0.0288***
	(0.0261)	(0.0145)	(0.0110)	(0.0156)	(0.00712)	(0.00772)	(0.0154)	(0.00770)	(0.00857)
L2.Col	-0.0961***	-0.0738***	-0.0604***	-0.00877	-0.00428	0.00363	-0.0886***	-0.0799***	-0.0454***
	(0.0273)	(0.0102)	(0.0147)	(0.0198)	(0.00819)	(0.00918)	(0.0127)	(0.0127)	(0.0137)
L.Cash#L.BLS	0.0296			-0.0280			0.0981**		
	(0.0398)			(0.0185)			(0.0384)		
L2.Lev#L.BLS	0.0222*			0.00384			-0.0263***		
	(0.0113)			(0.00479)			(0.00419)		
L2.Col#L.BLS	0.0220			0.00886			0.00784**		
	(0.0155)			(0.00600)			(0.00286)		
L.Cash#L.Sov		0.253***			-0.0262			0.105***	
		(0.0795)			(0.0157)			(0.0336)	
L2.Lev#L.Sov		0.0766***			0.00373**			-0.0209***	
		(0.0199)			(0.00177)			(0.00323)	
L2.Col#L.Sov		0.0340			0.00261			-0.0156***	
		(0.0221)			(0.00193)			(0.00258)	
L.Cash#L.Dis			0.0237***			-0.00933			0.0219***
			(0.00756)			(0.00623)			(0.00593)
L2.Lev#L.Dis			0.00259			-0.00200			-0.0128***
			(0.00261)			(0.00129)			(0.00139)
L2.Col#L.Dis			-0.00136			-0.00174			-0.0145***
			(0.00284)			(0.00147)			(0.00145)
Observations	284,991	360,936	360,936	398,153	480,972	480,972	697,141	760,876	760,876
R-squared	0.901	0.886	0.886	0.842	0.823	0.823	0.853	0.842	0.842
Year*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Table C3. Cash flows and leverage lagged by 3 years

		France			Spain			Italy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales	0.420***	0.410***	0.410***	0.466***	0.456***	0.456***	0.514***	0.504***	0.504***
	(0.0229)	(0.0229)	(0.0229)	(0.0135)	(0.0132)	(0.0132)	(0.0121)	(0.0124)	(0.0124)
L3.Cash	-0.0443	-0.0880***	-0.0784***	0.291***	0.187***	0.210***	0.0767	0.0797**	0.149***
	(0.0575)	(0.0248)	(0.0235)	(0.0771)	(0.0517)	(0.0557)	(0.0664)	(0.0377)	(0.0231)
L3.Lev	-0.0504***	-0.00946	-0.00109	-0.0128	-0.00927	0.00224	0.0461***	0.0239***	0.0328***
	(0.00977)	(0.00565)	(0.00734)	(0.0180)	(0.00799)	(0.00899)	(0.0113)	(0.00795)	(0.00936)
L3.Cash#L.BLS	-0.0210			-0.0774***			0.0323		
	(0.0330)			(0.0217)			(0.0271)		
L3.Lev#L.BLS	0.0446***			0.00833			-0.0155***		
	(0.00552)			(0.00581)			(0.00250)		
L3.Cash#L.Sov		0.0308			-0.0471**			0.0623*	
		(0.0708)			(0.0179)			(0.0313)	
L3.Lev#L.Sov		0.0881***			0.00746**			-0.0183***	
		(0.0121)			(0.00313)			(0.00242)	
L3.Cash#L.Dis			0.000295			-0.0292***			0.00443
			(0.00687)			(0.00814)			(0.00682)
L3.Lev#L.Dis			0.0131***			-0.000642			-0.00941***
			(0.00177)			(0.00168)			(0.00128)
Observations	380,696	415,880	415,880	502,651	540,387	540,387	814,666	844,559	844,559
R-squared	0.893	0.887	0.887	0.818	0.814	0.814	0.841	0.837	0.837

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Table C4. Cash flows and leverage lagged by 4 years

	France			Spain			Italy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales	0.420***	0.420***	0.421***	0.470***	0.470***	0.470***	0.521***	0.521***	0.521***
	(0.0217)	(0.0218)	(0.0218)	(0.0126)	(0.0126)	(0.0126)	(0.0126)	(0.0126)	(0.0126)
L4.Cash	-0.0513	-0.0663**	-0.0666**	0.296***	0.138***	0.161***	0.0760	0.0437	0.138***
	(0.0558)	(0.0287)	(0.0250)	(0.0679)	(0.0487)	(0.0525)	(0.0600)	(0.0396)	(0.0286)
L4.Lev	-0.0463***	0.0151*	0.0282***	0.00490	0.0159**	0.0247***	0.0213*	0.0224***	0.0295***
	(0.0114)	(0.00749)	(0.00945)	(0.0156)	(0.00764)	(0.00860)	(0.0113)	(0.00799)	(0.00874)
L4.Cash#L.BLS	-0.00970			-0.0978***			0.00252		
	(0.0305)			(0.0195)			(0.0213)		
L4.Lev#L.BLS	0.0509***			0.00859			-0.00447		
	(0.00478)			(0.00535)			(0.00273)		
L4.Cash#L.Sov		-0.00569			-0.0583***			0.0269	
		(0.0658)			(0.0167)			(0.0256)	
L4.Lev#L.Sov		0.0839***			0.00747**			-0.00929***	
		(0.00987)			(0.00289)			(0.00269)	
L4.Cash#L.Dis			-0.00157			-0.0339***			-0.0148**
			(0.00757)			(0.00691)			(0.00536)
L4.Lev#cL.Dis			0.0103***			0.000533			-0.00528***
			(0.00269)			(0.00158)			(0.00141)
Observations	364,176	364,176	364,176	480,959	480,959	480,959	744,393	744,393	744,393
R-squared	0.894	0.894	0.894	0.820	0.820	0.820	0.848	0.848	0.848

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.

Table C5. Impact of country-specific credit constraints on TFP: controlling for reliance on external finance: countries

		France			Spain			Italy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sales	0.412***	0.395***	0.395***	0.445***	0.426***	0.426***	0.498***	0.479***	0.479***
	(0.0261)	(0.0260)	(0.0260)	(0.0131)	(0.0123)	(0.0123)	(0.0137)	(0.0140)	(0.0140)
L.Cash	-0.375	-0.162	-0.0836	0.471**	0.684***	0.572***	0.303	0.295	0.562**
	(0.259)	(0.120)	(0.115)	(0.224)	(0.192)	(0.194)	(0.422)	(0.293)	(0.258)
L2.Lev	0.0314	0.0503	0.0338	0.0204	-0.0359	-0.0232	-0.0141	-0.0566**	-0.0423*
	(0.0679)	(0.0580)	(0.0423)	(0.0828)	(0.0369)	(0.0444)	(0.0283)	(0.0214)	(0.0211)
EF#L.Cash	0.372	0.159	0.122	0.00133	-0.232	-0.106	-0.223	-0.142	-0.339
	(0.236)	(0.0983)	(0.0961)	(0.198)	(0.169)	(0.170)	(0.337)	(0.250)	(0.230)
EF#L2.Lev	-0.0910	-0.0867	-0.0669	-0.0747	-0.0136	-0.0208	0.0769***	0.0779***	0.0715***
	(0.0668)	(0.0565)	(0.0410)	(0.0805)	(0.0378)	(0.0455)	(0.0262)	(0.0196)	(0.0191)
L.Cash#L.BLS	0.210			0.0605			0.135		
	(0.150)			(0.0791)			(0.148)		
L2.Lev#L.BLS	0.000838			-0.0154			-0.0267***		
	(0.0329)			(0.0243)			(0.00734)		
EF#L.Cash#cL.BLS	-0.180			-0.107			-0.0504		
	(0.137)			(0.0706)			(0.112)		
EF#L2.Lev#cL.BLS	0.0331			0.0278			-1.18e-05		
	(0.0320)			(0.0240)			(0.00727)		
L.Cash#L.Sov		0.620*			-0.0378			0.252	
		(0.303)			(0.0956)			(0.165)	
L2.Lev#L.Sov		-0.0383			0.00429			-0.0283***	
		(0.105)			(0.0117)			(0.00762)	
EF#L.Cash#L.Sov		-0.419			-0.00275			-0.136	
		(0.256)			(0.0877)			(0.125)	
EF#L2.Lev#L.Sov		0.0994			0.00307			-0.00140	
		(0.102)			(0.0121)			(0.00730)	
L.Cash#L.Dis			0.0709**			0.0261			0.0183
			(0.0295)			(0.0370)			(0.0398)
L2.Lev#L.Dis			0.00428			-0.00268			-0.0153***
			(0.0124)			(0.00782)			(0.00529)
EF#cL.Cash#L.Dis			-0.0588**			-0.0493			0.00606
			(0.0267)			(0.0339)			(0.0314)
EF#L2.Lev#L.Dis			0.00556			0.00377			0.00165
			(0.0120)			(0.00819)			(0.00509)
Observations	355,406	421,453	421,453	483,058	557,124	557,124	784,323	840,649	840,649
R-squared	0.895	0.886	0.886	0.801	0.790	0.790	0.823	0.815	0.815
Firm FE	yes	yes	yes	yes	yes	yes			
Sector-time FE	yes	yes	yes	yes	yes	yes			

Note: Standard errors clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1.