Identifying Financial Constraints from Production Behavior*

Laurens Cherchye[†] Bram De Rock[‡] Annalisa Ferrando[§]
Klaas Mulier[¶] Marijn Verschelde[‖]

September 28, 2018
PRELIMINARY VERSION

Abstract

Farre-Mensa and Ljungqvist (2016) show that the existing and widely used measures of financial constraints are inadequate and fail to measure financial constraints. We propose a new measure that recovers firm-year level financial constraints from firms' production behavior. In particular, we measure financial constraints as the profitability that profit maximizing firms forgo when binding constraints on input costs impede them from using the optimal level of inputs and technology. We validate our measure using a unique dataset that combines firms' balance sheets from 2005-2015 with direct information on firms' self-reported financial constraints between 2010 and 2015 in five Euro Area countries. Our measure nicely recovers the country-specific trends of financial constraints during the financial crisis and the sovereign debt crisis. Furthermore, we show that our measure correlates positively and strongly with loan rejection and discouragement and other direct measures of financial constraints.

*The authors would like to thank Nico Dewaelheyns and Angelos Theodorakopoulos for useful comments. Laurens Cherchye gratefully acknowledges the European Research Council (ERC) for his Consolidator Grant 614221. Bram De Rock gratefully acknowledges the FWO and FNRS for their support. The views expressed are solely those of the authors and do not necessarily represent the views of the European Central Bank or the National Bank of Belgium.

[†]Katholieke Universiteit Leuven. e-mail: laurens.cherchye@kuleuven.be.

[‡]ECARES, Université libre de Bruxelles and Katholieke Universiteit Leuven, e-mail: bderock@ulb.ac.be.

[§]European Central Bank, e-mail: annalisa.ferrando@ecb.int.

[¶]Ghent University and National Bank of Belgium, e-mail: klaas.mulier@ugent.be.

[‖]IÉSEG School of Management, LEM (UMR-CNRS 9221) and Katholieke Universiteit Leuven, e-mail: m.verschelde@ieseg.fr.

1 Introduction

Resolving financial constraints is a major policy concern. Financial constraints increase the wedge between the cost of internal and external financing, and hence affect firms' investment and employment decisions (Chodorow-Reich, 2014; Amiti and Weinstein, forthcoming). Therefore, for policy makers it is crucial to dispose of a measure that adequately tracks the level and evolution of financial constraints to be able to intervene timely and effective. For researchers, the adequacy of the measure is equally important as it will determine the conclusions that will be drawn.

Unfortunately, recent research by Farre-Mensa and Ljungqvist (2016) shows that the existing measures of financial constraints fail to adequately recover financial constraints. These measures, including popular indices developed by Kaplan and Zingales (1997), Whited and Wu (2006), and Hadlock and Pierce (2010), have in common that they are proxy variable approaches that try to measure financial constraints by a combination of observable characteristics. However, in practice, many unobservable characteristics also play an important role (e.g. management quality, customer dependence, bank lending standards, overall liquidity in the financial system, etc.).

In this paper, we take an alternative approach by recovering financial constraints from the actual optimizing behavior of profit maximizing firms. We build our identification strategy on the findings that for homogeneous sets of firms, firm growth constraints have predominantly a financial nature (see e.g. Beck et al. (2005)). Stated differently, binding input cost constraints reflect a highly inelastic supply of external finance within narrowly defined sets of firms. A distinguishing feature of our methodology with investment-based approaches is that we consider constraints on all observed input costs (and not only tangible fixed assets), while acknowledging for unobserved differences in productivity across firms. In particular, we recover financial constraints as the firms' foregone profitability due to binding input cost constraints that prohibit them to use the optimal level of inputs and technology.

We measure firm-year level financial constraints for more than 120,000 manufacturing firms in five Euro Area countries (Belgium, Germany, France, Italy, and Spain). We use detailed balance sheet and profit & loss account information from Orbis Europe and have information from 2005 to 2015, totaling nearly 600,000 observations. We match this balance sheet information with the responses of firms that participated in the Survey on Access to Finance of Enterprises (SAFE) conducted by the European Central Bank and the European Commission. The SAFE database includes information on whether firms faced rejections on actual applications for external financing, whether firms were discouraged to apply for external financing, or whether they had no need at all for external financing due to sufficient internal financing available.

We perform a number of analyses to shed light on the informational content and usefulness of our new financial constraints measure. First, looking across firms, we show that our financial constraint measure correlates positively and significantly with the rejection on firms' applications for external finance. Our measure shows higher values of financial constraints when firms recently had a rejected application for bank loans (or credit lines, or trade credit, for instance). Also firms that indicate a need for external finance, but that were discouraged to apply are more financially constraint. These results hold even after controlling for a wide battery of observable characteristics known to be important for access to external finance, indicating that our new measure captures more information on financial constraints than merely the (financial) characteristics observable to the econometrician.

Second, looking over time, our measure indicates that on average financial constraints declined from 2005 to 2007 and skyrocketed in 2008 and 2009 after the onset of the global financial crisis. After a small decline in 2010, our measure shows that financial constraints increased further during the sovereign debt crisis to a maximum in 2011 and 2012, after which our measure reveals a downward trend in financial constraints. Furthermore, breaking the information down to the country-level, we find that the global financial crisis, and especially the sovereign debt crisis, exacerbated financial constraints in Spain and Italy, compared to Belgium, Germany and France.

Third, we try to falsify our measure and relate it to a number of non-financial constraints that firms face, such as lack of product demand, regulation, fierce competition, etc. We find that our measure does not pick up any of these other obstacles that firms might face. This strengthens our believe that our measure is able to isolate the firms' financial constraints.

Fourth, we observe behavior of financially constrained firms that is consistent with being financially constrained. We find that firms with higher measured financial constraints invest significantly less in tangible fixed assets, are constraint in their labor choice, rely more intensively on credit from suppliers, and grant less credit to customers.

Finally, we compare our measure of financial constraints with the three most popular and widely used indices in the literature. The correlation between our measure and the Kaplan-Zingales index is less than 6 percent. The correlation with the Whited-Wu index is 23 percent and with the Hadlock-Pierce index 16 percent. Although we are aware that a low correlation does not prove the adequacy of FC as a measure of financial constraints, a (very) high correlation would likely indicate that our measure has the same flaws as the existing measures as shown by Farre-Mensa and Ljungqvist (2016).

Our paper contributes to the extant literature on financial constraints. One of the earliest approaches to measure indirectly financial constraints was to classify firms according to a characteristic based on information asymmetry (e.g. size, credit rating, or industrial group affiliation) or based on revealed financing needs (e.g. dividend payout). The virtue of these measures was demonstrated by the higher investment-cash flow sensitivity of firms classified as constrained (see for instance Fazzari et al. (1988); Hoshi et al. (1991) and Carpenter et al. (1994, 1998)). The validity of this approach was later heavily criticized, starting by Kaplan and Zingales (1997) who built a text-based measure of financial constraints derived from the CEO's financial statement that accompanies the annual income statement of 49 quoted firms, known as the KZ-index (Kaplan and Zingales, 1997; Lamont et al., 2001). Later, Whited and Wu (2006) constructed an index (WW-index) of financial constraints, which is derived from an economic investment model. Hadlock and Pierce (2010) and Hoberg and Maksimovic (2014) have studied the content of these indices using larger and longer samples. Overall, their results suggest that most components of the KZ-index and WW-index do not (or no longer) relate to financial constraints, leading Hadlock and Pierce (2010) to propose an index based solely on size and age (HP-index). Recently, Farre-Mensa and Ljungqvist (2016) came to the conclusion that none of the five discussed proxy variable approaches (KZ-index, WW-index, HP-index, dividend payout and credit rating) accurately measure financial constraints. By proposing a production behavior based methodology as full-fledged alternative for recovering financial constraints, we provide an accurate picture of financial constraints. We show that our methodology is not only a counterfactual framework without a priori parametric assumptions on the production process of firms, but also provides explanatory power beyond existing indicators of financial constraints.

The remainder of the text is structured as follows. In Section 2, we propose the methodology to recover financial constraints from firms' production behavior while correcting for unobserved heterogeneity in productivity (and the implied simultaneity issue). In Section 3, we describe the data and discuss the empirical set-up. In Section 4, we validate our advocated methodology using the ECB's SAFE questions and by considering a.o. the country-specific effects of '07-'08 financial crisis and the sovereign debt crisis on financial constraints.

2 Methodology

Our strategy to recover financial constraints is based on the actual production behavior of profit maximizing firms and thus requires production function identification. Seminal work of Marschak and Andrews (1944) and Olley and Pakes (1996) shows that input choices of firms can depend on productivity, implying a simultaneity issue when this dependency is disregarded. We follow Cherchye et al. (2018) by considering productivity as latent input costs that may be chosen endogenously and usually have a technological nature (e.g., intangibles). When information on input costs (including latent inputs) is complete, there is no unobserved heterogeneity in productivity. Conversely, incomplete information on input costs implies unobserved heterogeneity that may cause an endogeneity issue. In Section 2.1., we show how to recover financial constraints from production data, while taking into account unobserved heterogeneity in productivity. In Section 2.2., we discuss how the framework of Cherchye et al. (2018), which focused on cost minimizing firms, can be extended to allow for nonparametric identification of unobserved productivity of profit maximizing firms that may face financial constraints. In section 2.3., we discuss the practical implementation of our proposed measure of foregone profitability due to financial constraints.

2.1 Recovering financial constraints from production behavior

Following the original ideas of Shephard (1974), McFadden (1978), Lee and Chambers (1986) and Färe et al. (1990)[1], we assume financial constraints as unobserved constraints on profit maximization. We identify financial constraints from the observed firms' production behavior, using the assumption that these constraints are potentially binding. Loosening these binding constraints is thus expected to raise firm profits.

No heterogeneity in productivity To sketch the basic intuition of our approach, we first assume a setting without unobserved heterogeneity in productivity across firm observations. That is, we assume that we observe all the inputs (and their corresponding costs). Our analysis starts from a dataset $S = \{\mathbf{W}_i, \mathbf{X}_i, P_i, Q_i\}_{i \in N}$, with $\mathbf{W}_i \in \mathbb{R}^M_{++}$ the observed input prices, $\mathbf{X}_i \in \mathbb{R}^M_{+}$ the observed input levels, $P_i \in \mathbb{R}_{++}$ the observed output price, and $Q_i \in \mathbb{R}_{++}$ the observed output level for a set of N firm observations.

Figure 1 shows a textbook example of profit maximizing firm behavior (with a single input, i.e. $M = 1$). It illustrates how to recover financial constraints from production

[1] See Blancard et al. (2006) for an extension of this methodology to differ between short- and long-run credit constraints.

data under the maintained assumption of profit maximization. All firms operate under the same technology, which is represented by the production function $Q = F(\mathbf{X})$. Next, we assume that firm j achieves a maximal profit when facing the prices P_i and $\mathbf{W}_i$, which implies that the hyperplane $\Pi_j = P_i Q - \mathbf{W}_i \mathbf{X}$ is tangent to the function F in the point $(\mathbf{X}_j, Q_j)$. If firm i faces the same prices, then the output Q_i and inputs $\mathbf{X}_i$ do not yield maximum profit, i.e. the hyperplane $\Pi_i = P_i Q - \mathbf{W}_i \mathbf{X}$ intersects the function F in the point $(\mathbf{X}_i, Q_i)$. In our approach, we take it that firm i reveals its financial constraint by its suboptimal input choice. In particular, as any choice of $\mathbf{X}$ between $\mathbf{X}_i$ and $\mathbf{X}_j$ implies more profit than Π_i, we identify that firm i's input cost is constrained by the upper bound $C^* = \mathbf{W}_i \mathbf{X}_i$.

FIGURE 1 HERE

Heterogeneity in productivity In practice, the empirical analysis of profit maximizing firm behavior is often complicated by unobserved heterogeneity in productivity (i.e., differences in intangible assets, R&D expenses, etc.). As we will explain in more detail below, we follow Cherchye et al. (2018) by modeling unobserved productivity variation in terms of latent input $\mathit{\Omega}$. The dataset S does not contain any information on this productivity term $\mathit{\Omega}$, but productivity does affect the firms' observed output and input choices. The production technology depends on both observed inputs $\mathbf{X}$ and the unobserved input $\mathit{\Omega}$, which implies $Q = F(\mathbf{X}, \mathit{\Omega})$. It is important to effectively account for the presence of heterogeneity in productivity in order to achieve an adequate empirical assessment of profit maximizing firm behavior.

Figure 2 extends our previous example and illustrates the relevance of explicitly accounting for heterogeneity in productivity. We assume that the firms i and j are characterized by different levels of productivity, Ω_i and Ω_j. In this case, the curves through the points i and j represent the corresponding projections of the production function $F(\mathbf{X}, \Omega)$. Clearly, the two firms i and j are characterized by different production possibilities in terms of the observed output Q and input $\mathbf{X}$, and our analysis of Figure 1 is no longer valid. In particular, we find that firm i's foregone profit loss due to financial constraints is lower when accounting for differences in latent input. Generally, erroneously omitting latent input can bias the estimated profit losses due to financial constraints in any unpredictable way.

Moreover, foregone profit estimates that omit latent inputs are subject to a simultaneity issue originating from the dependency of observed input choice on unobserved technological features (see Marschak and Andrews (1944) and Olley and Pakes (1996)).[2] Therefore, to identify financial constraints in terms of foregone profit, we explicitly include latent input into our profit maximization analysis. In particular, we treat it as an unobserved input that is endogenous to observed input choices.

FIGURE 2 HERE

2.2 Nonparametric identification of productivity

The starting ground for our identification of constrained production functions of profit maximizing firms are the original ideas of Shephard (1974), McFadden (1978), Lee and Chambers (1986) and Färe et al. (1990), who show testable implications

[2] The literature on the estimation and identification of production functions has paid considerable attention to developing techniques that address this dependency problem. Notable examples include Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009) and, more recently, Ackerberg et al. (2015) and Gandhi et al. (2016). These existing approaches require a (semi)parametric specification of the production technology, implying a potential functional form misspecification bias. The approach of Cherchye et al. (2018) that we use in the current paper avoids imposing parametric structure on the technological production possibilities.

without the imposition of a priori (often restrictive) parametric assumptions on the functional form of the production function. We bring the nonparametric identification of constraints on production functions to the empirical setting at hand by including unobserved heterogeneity in productivity that influences input choice decisions, resulting in a simultaneity issue.

Cherchye et al. (2018) proposed a full-fledged nonparametric method to identify production functions of cost minimizing firms that are characterized by unobserved heterogeneity in productivity.[3] The method avoids functional specification bias by not imposing any nonverifiable parametric structure on the production technology. It also avoids the simultaneity bias in a natural way by including the unobserved aspects of production (i.e. unobserved inputs) directly in the optimization problem. In this paper, we extend this framework of Cherchye et al. (2018) to the case of constrained profit maximization. This will allow us to nonparametrically identify financial constraints from the observed production behavior.[4]

As in Cherchye et al. (2018), we assume a production function $Q = F(\mathbf{X}, \mathit{\Omega})$, i.e. we consider latent input $\mathit{\Omega}$ as an endogenous choice variable for the firm. The firm's problem is to maximize profits by optimally choosing its output and inputs, which comprise both observed inputs and latent input. Given our specific research question, we assume profit maximization subject to financial constraints pertaining to the observed inputs. Particularly, we assume that the observed input cost cannot

[3] Cherchye et al. (2018) extend the micro-economic literature on nonparametric production analysis of Afriat (1972); Hanoch and Rothschild (1972); Diewert and Parkan (1983); Varian (1984) by introducing unobserved productivity that is endogenous to observed input choices.

[4] The profit maximization framework as pursued in this paper is less general than the cost minimization framework of Cherchye et al. (2018). To operationalize our model of constrained profit maximization through linear programming, we assume that different firm observations face the same price for latent input.

exceed some predefined level C.[5] This gives the optimization problem

$$(OP) \qquad \max_{\mathbf{X},\Omega} PF(\mathbf{X},\Omega) - \mathbf{WX} - \Omega \text{ s.t. } \mathbf{WX} \leq C.$$

Checking consistency with this optimization problem requires identifying the unknown production technology F of the firm, the latent input Ω and the budget constraint C. Throughout, we will assume that all input-output combinations with observed cost below C (for the given prices $\mathbf{W}_i$) are feasible under the prevailing financial constraints. The optimization problem is associated with testable implications for the dataset S with N firm observations, which contains all the information on observed production behavior that is available to the empirical analyst. In Appendix A, we show the characterization of the optimization problem in empirical settings and show that it can be easily operationalized in noisy settings using a simple linear program.

2.3 Practical implementation.

Financial constraints as foregone profitability To facilitate comparison across firms, we use profitability (i.e., revenues over costs) as our metric of firms' profits. Focusing on profitability allows us to naturally scale profit differences.[6] However,

[5] We remark that our particular empirical set-up makes that we cannot explicitly model financial constraints related to the unobserved inputs. As we have no information on the latent input, it is empirically meaningless to impose restrictions on the associated costs. Of course, in reality there may well be financial constraints related to these unobserved variables. In such cases, our approach implicitly assumes that these constraints are sufficiently correlated with those on the observed inputs.

[6] Generally, analyzing profitability (i.e., revenues over costs) is exactly equivalent to analyzing profit (i.e., revenues minus costs) only when the production function is characterized by constant-returns-to-scale (CRS). In our empirical application, we consider five firm size groups within narrowly defined industries and, therefore, we may reasonably expect that profitability measures

our methodology is general in that alternative profit metrics could be used as well.

Assume that a firm observation j achieves a higher profitability than the firm observation i at the prices $(\mathbf{W}_i, P_i)$ that apply to i. When computing the associated foregone profitability due to financial constraints – our indicator of financial constraints FC – of firm i relative to firm j, it is important to effectively account for the possibility of unobserved heterogeneity in productivity. Particularly, under the assumption of no unobserved heterogeneity (i.e. complete information on the input costs), the financial constraint is defined as

$$FC_i^{**} = \frac{P_i Q_j}{\mathbf{W}_i \mathbf{X}_j} - \frac{P_i Q_i}{\mathbf{W}_i \mathbf{X}_i}. \tag{1}$$

By contrast, when inputs are only partially observed, we can account for heterogeneity in productivity by explicitly including latent input in the analysis. This obtains the alternative financial constraint measure

$$FC_i^{*} = \frac{P_i Q_j}{\mathbf{W}_i \mathbf{X}_j + \Omega_j} - \frac{P_i Q_i}{\mathbf{W}_i \mathbf{X}_i + \Omega_i}. \tag{2}$$

From our discussion above, there is no reason to suspect that FC_i^{**} equals FC_i^{*}, resulting in an omitted variable bias when unobserved input costs are not acknowledged for. In our practical application, we can compute the measure FC_i^{*} by using the estimates of latent input that we defined before.

Measuring financial constraints Relaxing financial constraints opens the door for production possibilities that go together with higher profitability. To empirically

provide adequate information on the latent constraints on profit maximization. Stated differently, for our application, we assume a CRS assumption "*locally*", implying that it only has to hold for the given firm size group.

measure the foregone profitability due to prevailing financial constraints, we compare the actual profitability with a measure of achievable profitability under less stringent financial constraints.

For each firm i, we use as our measure of achievable profitability the average profitability (evaluated at the given prices $(\mathbf{W}_i, P_i)$) defined over all firm observations with more costly inputs than firm i. It represents the expected profitability when loosening firm i's financial constraints. Then, we specify the following measure of financial constraints:

$$FC_i = \max\left(0, Average_{j \in T_i^{beyond}}\left(\frac{P_i Q_j}{\mathbf{W}_i \mathbf{X}_j + \Omega_j}\right) - \frac{P_i Q_i}{\mathbf{W}_i \mathbf{X}_i + \Omega_i}\right), \quad (3)$$
$$\text{with } \boldsymbol{T}_i^{beyond} = \{j | \mathbf{W}_i \mathbf{X}_i \leq \mathbf{W}_i \mathbf{X}_j\}.$$

In this expression, the max operation excludes negative values for FC_i, i.e. negative foregone profitability. This accounts for the possibility that, in practice, firm i's actual profitability may well exceed the expected profitability (which is defined over firm observations with at least the same cost level as i).

As a final note, other summary statistics than the average may equally be used as measures of achievable profit. For example, alternative candidates are the median, maximum or some other quantile of the profitability distribution that is defined over the firm observations with more costly inputs than firm i. As explained above, our measure of achievable profit reflects the "expected" profitability for firm i under weaker financial constraints. In our opinion, the difference between this expected profitability and firm i's actual profitability provides an intuitive measure of foregone profit due to financial constraints.

3 Application set-up and data

The dataset is compiled by the European Central Bank and Bureau van Dijk and augments the responses of firms that participated in the Survey on the Access to Finance of Enterprises (SAFE) with detailed balance sheet and profit & loss information available in Orbis Europe between 2005-2015. The survey data are available from the 3rd wave of the survey (Q2-Q3 2010) until the 14th wave (Q4 2015-Q1 2016) for on average 6,500 firms in each wave, of which 90 percent are SMEs. Bureau van Dijk is not able to match every firm in SAFE with their balance sheet, but the matching is quite high (on average around 80%, but varies across countries and sectors).

From this dataset, we exclude all non-manufacturing firms and due to the computational intensity of our linear program we further limit our sample to firms operating in the five largest euro area economies: Germany, France, Italy, Spain, and Belgium[7]. This combined dataset has the major advantage that it allows us to construct our new financial constraints measure (FC) from the production data included in Orbis Europe and validate its content with direct questions on financial constraints such as loan application outcomes included in the SAFE survey.[8]

TABLES 1 and 2 HERE

Table 1 shows how we define inputs, outputs and their prices. We include as output the deflated sales revenue and as inputs the number of employees in full time

[7] The Netherlands is actually the fifth largest euro area economy, but the coverage of firms in Orbis Europe is poor in the Netherlands, therefore we replace the Netherlands by the sixth largest euro economy, Belgium.

[8] From 2005 onwards, the sample composition of firms in Orbis Europe with non-missing production data is stable for the five included countries.

equivalents (FTE), deflated tangible fixed assets and deflated materials use. For the input prices, we use respectively the price of labor[9], and the nace 2-digit deflators of intermediary inputs and tangible fixed assets.[10] To obtain homogenous sets of firm observations as basis of the FC estimation, we compare profitability only within narrowly defined industry and firm size classes and within countries. We consider nace 4-digit industries (nace rev. 2 classification) and the firm size groups follow the European Commission classification of firm size categories. We thus separate micro, small, medium and large firms. In addition, we separate very small firms from small firms to deal with the large heterogeneity across small firms in terms of observables.[11] We only estimate FC_{it} when the number of observations in a country-industry-firm size group is equal to or more than 100, resulting in 563 country-sector linear programs we ran with on average 1,093 comparison partners at the country-sector-firm size level.[12] We successfully estimated FC_{it} for 667,631 firm observations of 132,805

[9] The price of labor is obtained by dividing labor cost by the number of employees in FTE.

[10] We use nace 2-digit industry-wide deflators based on EU KLEMS and eurostat. To avoid effects of extreme outliers and extreme noise in the whole dataset, we limit the sample to observations of firms with at least five employees. We limit the sample to firms with a book year equal to 12 months. We removed the highest and lowest percentile of the level and growth rates, at the country-sector-firm size level, for the output, observed inputs, the price of labor, observed profit, observed costs, observed profitability, share of respectively materials, labor and capital in observed costs, labor productivity, capital productivity (with capital defined as tangible fixed assets) and materials productivity. We excluded labor from the cleaning on levels. We also removed clear erroneous reporting by limiting the sample to input-output observations with values over 1,000 euro and labor price with values over 10,000 euro. Smaller firms are known to be underrepresented in the AMADEUS dataset and have a higher probability to be excluded from the analysis due to missing values.

[11] We consider five firm size groups. (1) Large firms, (2) Medium sized firms (labor in FTE lower than 50 and revenues lower than 50 million euro or total assets lower than 43 million euro), (3) Small firms (labor in FTE lower than 50 and revenues or total assets lower than 10 million euro). (4) Very small firms (small firms with labor in FTE lower than 20), (5) Micro firms (labor in FTE lower than 10 and revenues or total assets not exceeding 2 million euro).

[12] To allow for moderate-to-considerable random noise, we set goodness-of-fit parameter $\theta = 0.9$ (see Appendix A for a discussion). To acknowledge for the fact that inputs are not perfectly flexible, we limit the set of comparison partners for each firm to those with a similar labor cost share and capital cost share in comparison to the firm in question. In particular, only firms with labor and

firms.[13] After having run all the linear programs, we dropped the top percentile of country-industry-firm size groups in terms of average cost share of latent input (to remove sectors with surrealistically high latent input levels, due to outliers that were not captured in the cleaning process), removed observations with no financial data and dropped firms with no two consecutive observations (as we use lags as independent variables in our regression analyses).

In our final sample used for validation testing and for which we provide summary statistics in Table 3, we have the required balance sheet information for 124,302 firms that are observed on average 4,8 times between 2005 and 2015, implying a total number of 599,778 observations.[14] 2,671 of these firms participated on average 1.6 times in the SAFE survey, implying a total number of 5,525 observations. The panel component in the SAFE survey is thus rather weak, which limits the application of any analysis based on popular panel estimation techniques, such as (firm) fixed effects estimators.

TABLE 3 HERE

While the most popular measures of financial constraints are tailored towards listed firms, our measure uses production data which is in large-scale available for both listed and (usually smaller) non-listed firms. As such, our dataset consists of both small and large firms, whereof a vast majority were never listed (99,8 percent of the sample). We consider 153,438 observations of micro firms, 315,348 observations of

capital cost shares higher (lower) than 0.75 (1.25) times the respective cost shares of the firm in question are considered as potential comparison partners in our linear program to estimate Ω and in the estimation of FC.

[13] We ran the linear programs for the sample of 754,167 observations of 150,040 firms, but we excluded from the further analysis all firm observations for which the linear program at the country-sector level was not able to close-to-rationalize the data using a goodness-of-fit parameter $\theta = 0.9$.

[14] All descriptive statistics are very similar when considering the original cleaned dataset.

small firms (whereof 229,701 observations of very small firms), 108,405 observations of medium firms and 22,587 observations of large firms. On average, the number of employees in FTE is 57.82, ranging from 5 to 71,205. In addition, our dataset covers both starting and well-established firms, with firm age covering the range between 1 and 181. The sample is composed of 21.6 percent young firms (age lower or equal than 10), 44.2 percent mature firms (age higher than 10 and lower or equal than 25) and 34.2 percent old firms (age higher than 25).
We find that financial constraints as measured as foregone profitability is on average 0.107, meaning that we estimate firms to have a loss due to financial constraints of 10,7 percentage points of profitability, with the latter including latent input in the denominator. For 30 percent of observations, our estimates show no foregone profitability due to binding financial constraints, indicating that moving towards more costly production processes is not expected to increase profitability for these firm observations. Financial constraints seem to be quite persistent. Regressing FC on its lag reveals an AR(1) component of 0.79.

Our FC estimates as summarized in Table 4 confirm the stylized fact that financial constraints are heterogeneous across firms and that this heterogeneity is related to firm characteristics. In particular, we confirm that smaller and younger firms are more likely to face financial constraints. The average FC for micro firms is 0.118, which is 3 percentage points higher than the average FC of medium and large firms. Young firms face on average 13.3 percent foregone profitability due to financial constraints, which is 4 percentage points higher than the FC of old firms. Comparison across countries should be considered with care due to differences in sample composition. Still, we can conclude that financial constraints are overall higher in Spain and Italy and relate in these countries more with firm size and firm age. In Italy, the connection between financial constraints and firm characteristics is most pronounced. Italian micro (small) firms face financial constraints that are 4.9 (3.8) percentage points higher than those of medium and large firms. Financial constraints of young firms are in Italy on average 4.2 percentage points higher than those of mature firms and 6 percentage points higher than the average FC of old firms. Last, results available upon request show that financial constraints of listed companies (1,045 firm observations) are on average 16 percent lower (i.e. 9.2 percentage points) than the financial constraints of private firms; and the financial constraints of delisted firms (131 firm observations) are on average 35 percent lower (i.e. 7.9 percentage points) than the financial constraints of private firms.

Next to the characteristics of financial constraints, we also find a robust relation between firm size, firm age and the log of latent input, with the latter capturing the level of unobserved inputs. Summary statistics available upon request show that large firms overall have higher levels of latent input. As discussed in Cherchye et al. (2018), latent input can be interpreted in terms of productivity. Our fully non-parametric estimates thus confirm the well-established positive correlation between measured productivity and firm size as discussed in a.o. Haltiwanger et al. (1999); Van Biesebroeck (2005); Forlani et al. (2016). Density plots available upon request show that this relation is present for each country considered.

TABLE 4 HERE

4 Empirical validation

In this section we investigate whether our new measure indeed captures the degree of financial constraints of firms. We design tests that look at several dimensions of our measure of financial constraints. We test whether our measure correlates with direct measures of financial constraints such as loan application outcomes, whether our measure correlates with variables that are believed to be determinants of financial constraints, whether our measure can recover the influences of macro-economic events such as the '07-'08 crisis and the sovereign debt crisis, whether our measure does not pick up other constraints (e.g. slacking product demand), whether our measure detects firm behavior that is consistent with financial constraints in a real effects context (e.g. investment behavior), and finally how our index relates to existing measures of financial constraints.

4.1 Self-reported measures of financial constraints

In this section, we test whether our measure correlates with five direct measures of financial constraints as reported by firms in the SAFE survey. To shed light on this, we regress the different survey based measures of financial constraints on our measure of financial constraints (FC) while controlling for various fixed effects:

$$Y_{i,c,s,t} = g(\alpha FC_{i,c,s,t}, \beta X_{i,c,s,t-1}, \nu_i, \mu_c, \lambda_j, u_{i,c,s,t}). \tag{4}$$

Where $Y_{i,c,s,t}$ represents five different survey-based measures of financial constraints. The first indicator concerns a dummy equal to 1 when a firm perceives Access to Finance to be its most pressing problem and 0 otherwise. The other four dummies concern Rejection or Discouragement, related to (a) Bank Loans, (b) Credit Lines, (c) Trade Credit, (d) Other Financing. These indicators take the value 1 when a firm was either (i) discouraged to apply for this source of external financing out of fear of rejection, (ii) when a firm applied for it but was rejected, or (iii) when a firm applied for it but had to refuse the offer because the borrowing costs were too high; and 0 when a firm applied for this source of external financing and got approved (see Table 1 for a detailed explanation of the dummies and Table 3 for summary statistics). $FC_{i,c,s,t}$ is our new financial constraints measure. $X_{i,c,s,t-1}$ is a vector containing lagged variables that are typically believed to be determinants of financial constraints, such as the firms' financial pressure, leverage, size, and age. The model further includes time fixed effects ν_i, country fixed effects μ_c, and nace 4-digit sector fixed effects λ_s. $u_{i,c,s,t}$ captures statistical noise.

TABLE 5: HERE

The results of the logit regressions are shown in Table 5 (marginal effects reported). All five survey based indicators show a statistically significant and strong positive relation with our proposed FC measure. The first column sheds light on the relation between our FC measure and the probability that firms indicate that access to finance is their most pressing problem. A one standard deviation higher FC relates to a 1.4 percentage point higher probability of perceiving access to finance as the most pressing problem, which is an increase of 11.6 percent relative to the average. After the inclusion of country, industry and year fixed effects, the estimates show a 1 percentage point increase, equaling to a 9 percent increase. Panel C shows that this association turns statistically insignificant when we include observed characteristics that determine financial constraints. Still, results as described in column 1 support the idea that FC measures financial constraints.

Columns 2 to 5 of Table 5 show the relation between FC and four indicators on external financing rejection or discouragement (bank loan, credit line, trade credit, and other financing). All four indicators show a positive and significant relation with FC. These relations remain economically and statistically significant when we control for fixed effects at the country, sector and year level (Panel B) and when we include observables that relate to financial constraints (Panel C). The results in Panel C indicate that our new measure captures more information on financial constraints than merely the observable characteristics.

In particular, the second column shows that our FC measure relates positively to the firm's bank loan rejection or discouragement probability. One standard deviation higher financial constraints (FC) is associated with a 6 percentage points higher rejection or discouragement probability, which is a 26.9 percent increase (relative to the unconditional mean of 23 percent). After controlling for fixed effects and control variables, we still find a 5 percentage point higher probability, equaling to a 21.7 percent increase. Similar patterns arise for rejection or discouragement related to credit lines, trade credit, and other financing. We respectively find that a one standard deviation higher FC corresponds to respectively a 3.2, 2.4 and 3.9 percentage point higher probability of rejection or discouragement (after controlling for fixed effects and control variables), equaling to changes over 10 percent. In Table 10 in the Appendix, we show that these results hold when one drops the discouraged firms from the previous measures, hence only considering the rejection or approval of applications for external finance (columns 1 to 4), or when one adds to the previous measures also firms with no need for external financing due to sufficient internal financing available (columns 5 to 8). Our measure – that solely requires production data – thus recovers a substantial part of the heterogeneity in financial constraints across observations at the firm-year level.

4.2 Determinants of financial constraints

A second test is whether our measure of financial constraints correlates with variables that are typically believed to be determinants of financial constraints. To this end, we run regressions on $Y_{i,c,s,t}$, representing six different measures of financial constraints (see (5)). $X_{i,c,s,t-1}$ is a vector containing lagged variables that are typically considered to be determinants of financial constraints, such as the firms' financial pressure (i.e. the inverse of the interest coverage ratio), leverage, size and age. ν_i is a set of time fixed effects, μ_c is a set of country fixed effects, and λ_s is a set of nace 4-digit sector fixed effects and $u_{i,c,s,t}$ captures random noise. Subscript i indicates firm, c indicates country, s indicates sector at the nace 4-digit level, and t indicates year.

$$Y_{i,c,s,t} = g(\beta X_{i,c,s,t-1}, \nu_i, \mu_c, \lambda_s, u_{i,c,s,t}). \tag{5}$$

In the last five columns of Table 6 we look at how the selected variables correlate with the five direct measures of financial constraints as reported by firms in the survey and transform model (5) into a logistic regression model. In the first column, we use OLS to study how our new measure of financial constraints relates with the selected variables. Table 6 shows that our new measure of financial constraints relates in the same way to observable (financial) characteristics that are typically believed to be determinants of financial constraints as, for instance, an indicator of loan rejection or loan discouragement.

Our FC measure and the survey based measures show that firms that face higher financial pressure and have a higher leverage are overall more financially constrained. This is in line with what we expected since higher financial pressure implies that firms already need a large part of their earnings before interest and taxes to service their current financial debt, and thus have limited spare debt capacity. Firms with higher leverage are also more likely to face constraints on access to finance. First, a high leverage implies a low equity buffer, which could safeguard a firm from an unexpected negative shock. Second, a high leverage may also exacerbate agency conflicts between debt holder and shareholders. Further, Table 6 shows a negative relation between financial constraints and respectively firm age and firm size, as discussed in detail in section 3.

TABLE 6: HERE

4.3 Macro-economic events

Financial constraints might originate at the firm level (due to for instance insufficient equity or an underdeveloped business plan), but they might also originate at the macro-level. It has been shown for instance that firms report more financing obstacles in countries where the institutional development and the development of the banking sector is lower (Beck et al., 2006, 2007). Another example is the occurrence of a financial or a banking crisis which tends to amplify the financial constraints that firms face in an economy. The global financial crisis of '07-'08 led to the insolvency of many (large) banks throughout Europe. To avoid a dramatic increase in the financial constraints of the firms in their country (i.e. to avoid a spill-over from the financial to the real sector), governments bailed out the failing banks. As these failing banks were often very large, bailing them out led to a huge increase in the outstanding government debt of many countries. In Spain and Italy, this led the financial markets to question the solvency of the sovereign. Unfortunately, as banks tend to hold significant amounts of sovereign debt, in particular of the domestic sovereign, the stress in the Spanish and Italian banking sector was not relieved after the bail-out of the failing banks as it kicked right back in once their respective sovereign became under stress. In this section we study whether our measure is able to pick up the impact of a macro-economic event on the average level of financial constraints in an economy. The events that we consider are the financial crisis of '07-'08 and the sovereign debt crisis.

Figure 3 shows the evolution of FC over the considered time period for all countries together. The figure shows the percentage point differences with the average level in 2007 after filtering away influences from time-varying sample composition. Both the influence of the '07-'08 financial crisis and the sovereign debt crisis which started in 2010 are well recovered by our FC measure. Both our measure and the direct survey measure on Loan Rejection or Discouragement as documented in the SAFE survey show an inverse U shape pattern of financial constraints in the period 2010-2015 with as peak 2013.[15] The moderation of financial constraints from 2013 onwards is in line with a calming of the credit markets after the announced "*whatever-it-takes*" policy of the ECB to preserve the euro on July 26th, 2012 by the ECB president Mario Draghi.

FIGURE 3: HERE

[15] As the sample size for SAFE survey measures is small, we can only compare general trends over all firms. The discussed trends are robust for using the median instead of the mean.

In Figure 4, one can see that for the FC measure, this increase of financial constraints is particularly driven by Italy and Spain (which jointly represent more than 3 quarters of our firm-level observation), consistent with the idea that the sovereign debt crisis increased financial constraints in these two countries relative to the other considered countries.[16]

FIGURE 4: HERE

4.4 Financial constraints and non-financial constraints

One concern one might have about our new measure of financial constraints is whether we are not picking up other constraints firms might face (such as a drop in product demand for instance), rather than purely constraints of financial nature.

These are valid concerns that we mitigate by the design of our identification strategy, where we estimate the foregone profitability by comparing firms within the same country, within the same nace 4-digit industry, within the same size group. This way, for instance, we ensure that comparison firms face the same employment protection legislation and face similar product demand. Degryse et al. (2018) show that firms operating in the same industry, in the same location, that are of comparable size, have

[16] It should be noted that a comparison of the average levels of financial constraints *across* countries is difficult, as the sample composition is different. Further, our advocated measure of foregone profitability due to financial constraints relates to obstacles to finance and the influence of these obstacles on both technology choice and profitability, implying that our measure also takes into account the severity of the missed opportunities in a natural way. As such, for Germany, the higher average level of FC (compared to France for instance) may be the result of both higher levels and more heterogeneity in latent input compared to other countries. Descriptive statistics at the country level available upon request. As the sample composition *within* a country remains quite stable, analyzing the trend within countries does not require this caution.

similar credit demand. The differences in the firms' chosen inputs (and associated profitability) are thus likely to pertain to the differences in the degree to which firms' credit needs have been met.

We also try to falsify the content of our measure empirically and test whether it correlates positively with a number of non-financial constraints that firms might face. We test whether our measure correlates positively with lack of product demand, fierce competition, too high costs of production or labor, insufficient availability of skilled employees, and too rigid regulation. The results of these tests (which are performed in a similar way as the tests in Table 5) are shown in Table 7 below. As can be seen, we find that our measure does not pick up any of these other obstacles that firms might face, which strengthens our believe that our measure is able to isolate the firms' financial constraints.

TABLE 7: HERE

4.5 The real effects of financial constraints

In this section we aim to test whether we observe behavior of financially constrained firms that is consistent with being constrained. This may seem straightforward and too simplistic, but as Farre-Mensa and Ljungqvist (2016) show, this is not necessarily the case. In contrast to Farre-Mensa and Ljungqvist (2016), we do not have an instrument at hand that exogenously changed the need for debt financing, so we resort to testing the impact of such constraints on (a) firms' investment behavior (see Amiti and Weinstein (forthcoming), we consider the growth of deflated tangible fixed assets), (b) employment growth (see Chodorow-Reich (2014)), (c) Days Sales

Outstanding minus Days Payable Outstanding (DSO - DPO). The relation between financial constraints and input dynamics (a-b) is a direct consequence of input cost constraints, which we model in terms of foregone profitability. Ferrando and Mulier (2013) show that trade credit is used to manage firm growth by companies that face financial market imperfections. We expect firms that are more financially constrained to grant less credit to customers and to rely more on credit from suppliers (implying lower DSO minus DPO).

We test the real effects of financial constraints, using the following empirical model:

$$Y_{i,c,s,t} = \alpha FC_{i,c,s,t-1} + \beta X_{i,c,s,t-1} + \gamma_i + \nu_t + \mu_c + \lambda_s + u_{i,c,s,t}. \tag{6}$$

Where $Y_{i,c,s,t}$ represents real effects (a)-(e) as discussed above. $FC_{i,c,s,t-s}$ is our lagged financial constraints measure. $X_{i,c,s,t-1}$ is a vector containing the respective lag of indicator (a)-(e) and lagged variables that are typically believed to be determinants of financial constraints, such as the firms' financial pressure, leverage, size, and age. The model further includes time fixed effects ν_t, country fixed effects μ_c, and nace 4-digit sector fixed effects λ_s. $u_{i,c,s,t}$ captures random noise.

In line with the idea that our advocated financial constraints measure FC provides an accurate picture of financial constraints, Table 8 shows a negative relation between FC and investment, employment growth,and DSO minus DPO. These real effects of FC are robust for the inclusion of firm fixed effects. Economically, we find a moderate, yet non-negligible effect. A one standard deviation increase in financial constraints is estimated to decrease the log growth of tangible fixed assets by 0.05 standard deviation (0.03 when including firm FE) and decrease employment growth with 0.09 standard deviation (0.12 when firm FE are included). Further, a one standard deviation increase in financial constraints corresponds to a 0.01 standard deviation change of DSO minus DPO, with the results being robust for the inclusion of firm FE.

TABLE 8: HERE

4.6 Comparison with existing financial constraints indices

In this final section we compare our measure of financial constraints with three existing and widely used measures of financial constraints: the Kaplan-Zingales index, the Whited-Wu index, and the Hadlock-Pierce index. To investigate this, we look at 1,045 firm-year observations from the 207 listed companies that are included in our dataset.

TABLE 9: HERE

We first look at simple correlations between our measure of financial constraints and the three indices, which are reported in Panel A of Table 9. As can be seen, the correlations are rather low. The correlation between FC and the Kaplan-Zingales is less than 6 percent, while the correlation between FC and the Whited-Wu index is 23 percent and the Hadlock-Pierce index is 16 percent. Given that Farre-Mensa and Ljungqvist (2016) showed the inadequacy of the existing measures, this low correlation is not necessarily worrisome for our measure of financial constraints, perhaps on the contrary. Although we are aware that a low correlation does not prove the adequacy of FC as a measure of financial constraints, a high correlation would likely indicate that FC has the same flaws as the existing measures.

In panel B of Table 9 we try to find why the correlation between FC and the existing indices is so low and regress FC on the index components for each index. Columns 1 and 2 report the impact of the five components of the Kaplan-Zingales index (Q, long term book leverage, cash flow, dividends, cash holdings). Columns 3 and 4 report the impact of the six components of the Whited-Wu index (industry sales growth, sales growth, long term book leverage, cash flow, dividends, size). Columns 5 and 6 report the impact of the three components of the Hadlock-Pierce index (size, size squared, age).

As can be seen, FC seems positively but insignificantly related with Q, which is supposed to capture growth opportunities. To the same extent, FC seems to be somewhat positively related with industry sales growth and negatively with sales growth which are jointly supposed to capture growth opportunities in the Whited-Wu model. Opportunities play a similar role in our measure where firms will be particularly financially constrained when they operate in an environment where investments translate easily in more profits. Long term book leverage, which increases financial constraints in the Kaplan-Zingales index and the Whited-Wu index, appears to be unrelated to FC, in this sample of listed firms. Dividends seem to be negatively related to FC, but the results hold only in the cross-section and not when dividends are considered as a dummy.

The only two components that seem to be significantly related to FC in this sample are cash flow and firm size. Financial constraints decrease with both components. In the Hadlock-Pierce model, size is capped at 4,5 billion euro and enters positively because of the included quadratic term (without the quadratic term, size enters negatively). However, in contrast to the Hadlock-Pierce model, the relation between size and financial constraints appears to be concave in our model, instead of convex in their model.

5 Conclusion

Recently, Farre-Mensa and Ljungqvist (2016) showed the need for new financial constraint measures as none of the five most popular measures (KZ-index, WW-index, HP-index, dividend payout and credit rating) accurately measure financial constraints. In this paper, we propose to recover financial constraints from production behavior. The basis of our identification strategy is the difference between the actual observed production behavior of profit maximizing firms and the optimal production behavior of these profit maximizing firms. In a fully nonparametric fashion, we detect foregone profitability as the difference between actual profitability and the profitability level we estimate to be achievable when financial constraints were less stringent. For this, we first solve a simultaneity issue that arises due to the dependency of observed input choices on usually unobserved heterogeneity in productivity.

We apply our methodology on detailed firm-year level balance sheet and profit & loss information from Bureau van Dijk's AMADEUS dataset for the period 2005-2015 which we linked with the Survey on Access to Finance of Enterprises (SAFE) as collected by the ECB at the firm level for the period 2010-2015. We cover five euro area countries which differ in terms of macro-events. An empirical validation of our advocated financial constraints measure shows that our indicator indeed has an empirical bite. Our measure nicely picks up the financial constraint dynamics around the '07-'08 crisis and the sovereign debt crisis and relates strongly with direct survey measures of financial obstacles (e.g. loan rejections), even when we control for a wide battery of observable characteristics that are often presumed to relate to financial constraints. Further, our measure correlates as expected with well-recognized determinants of financial constraints and shows to correlate with dynamics related to firm growth and use of the trade credit channel. Overall, we show that we can recover a substantial part of the heterogeneity between firm-year observations in financial constraints with the sole use of widely available production data.

Our methodology has micro-economic foundations and provides an accurate picture of financial constraints. Still, further research is needed to obtain deeper insight into the heterogeneity across firms in how they are hindered by financial obstacles. We consider this paper as a starting ground for research on financial constraints that goes beyond partial indicators and makes direct use of the optimizing production behavior of firms. In our paper, we imposed few assumptions or data requirements. By adding (e.g. dynamic) structure to the methodology or by adding financial information, estimation can be tailored to the particular situation at hand and empirical identification of financial constraints could potentially be sharpened.

References

Ackerberg, D., Caves, K., Frazer, G., 2015. Identification properties of recent production function estimators. Econometrica 83 (6), 2411–2451.

Afriat, S., 1972. Efficiency estimation of production functions. International Economic Review 13 (3), 568–598.

Amiti, M., Weinstein, D., forthcoming. How much do bank shocks affect investment? Evidence from matched bank-firm loan data. Journal of Political Economy.

Beck, T., Demirgüç-Kunt, A., Maksimovic, V., 2005. Financial and legal constraints to growth: Does firm size matter? The Journal of Finance 60 (1), 137–177.

Beck, T., Demirguc-Kunt, A., Laeven, L., Maksimovic, V., 2006. The determinants of financing obstacles. Journal of International Money and Finance 25, 932–952.

Beck, T., Demirguc-Kunt, A., Martinez Peria, M. S., 2007. Reaching out: Access to and use of banking services across countries. Journal of Financial Economics 85 (1), 234–266.

Blancard, S., Boussemart, J. P., Briec, W., Kerstens, K., 2006. Short- and long-run credit constraints in french agriculture: A directional distance function framework using expenditure-constrained profit functions. American Journal of Agricultural Economics 88 (2), 351–364.

Carpenter, R. E., Fazzari, S. M., Petersen, B. C., 1994. Inventory investment, internal-finance fluctuations, and the business-cycle. Brookings Papers on Economic Activity (2), 75–138.

Carpenter, R. E., Fazzari, S. M., Petersen, B. C., Nov. 1998. Financing constraints and inventory investment: A comparative study with high-frequency panel data. Review of Economics and Statistics 80 (4), 513–519.

Cherchye, L., Demuynck, T., De Rock, B., Verschelde, M., 2018. Nonparametric production analysis with unobserved heterogeneity in productivity, KU Leuven, Department of Economics Discussion Paper Series 18.11.

Chodorow-Reich, G., 2014. The employment effects of credit market disruptions: Firm-level evidence from the 2008-09 financial crisis. Quarterly Journal of Economics 129, 1–59.

Degryse, H., De Jonghe, O., Jakovljevic, S., Mulier, K., Schepens, G., 2018. Identifying credit supply shocks with bank-firm data: Methods and applications.

Diewert, W., Parkan, C., 1983. Linear programming tests of regularity conditions for production frontiers. In: Eichhorn, W., Henn, R., Neumann, K., Shephard, R. (Eds.), Quantitative Studies on Production and Prices. Physica-Verlag, Würzburg.

Färe, R., Grosskopf, S., Lee, H., 1990. A nonparametric approach to expenditure-constrained profit maximization. American Journal of Agricultural Economics.

Farre-Mensa, J., Ljungqvist, A., 2016. Do measures of financial constraints measure financial constraints? The Review of Financial Studies 29 (2), 271–308.

Fazzari, S., Hubbard, R., Petersen, B., 1988. Financing constraints and corporate investment. Brookings Papers on Economic Activity 1, 141–195.

Ferrando, A., Mulier, K., 2013. Do firms use the trade credit channel to manage growth? Journal of Banking & Finance 37, 3035–3046.

Forlani, E., Martin, R., Mion, G., Muûls, M., 2016. Unraveling firms: Demand, productivity and markups heterogeneity. Tech. Rep. 293, National Bank of Belgium Working Paper Series 293.

Gandhi, A., Navarro, S., Rivers, D., 2016. On the Identification of Production Functions: How Heterogeneous is Productivity? Working paper, University of Western Ontario, Centre for Human Capital and Productivity (CHCP).

Hadlock, C. J., Pierce, J., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. Review of Financial Studies 23(5), 1909–1940.

Haltiwanger, J., Lane, J., Spletzer, J., 1999. Productivity differences across employers: The roles of employer size, age, and human capital. American Economic Review 89 (2), 94–98.

Hanoch, G., Rothschild, M., 1972. Testing assumptions of production theory: A nonparametric approach. Journal of Political Economy 80 (2), 256–275.

Hoberg, G., Maksimovic, V., 2014. Redefining financial constraints: A text-based analysis. Review of Financial Studies 28 (5), 1312–1352.

Hoshi, T., Kashyap, A., Scharfstein, D., 1991. Corporate structure, liquidity, and investment: Evidence from Japanese industrial groups. The Quarterly Journal of Economics 106(1), 33–60.

Kaplan, S. N., Zingales, L., 1997. Do financing constraints explain why investment is correlated with cash flow? Quarterly Journal of Economics 112, 169–216.

Lamont, O., Polk, C., Saa-Requejo, J., 2001. Financial constraints and stock returns. Review of Financial Studies 14(2), 529–554.

Lee, H., Chambers, R., 1986. Expenditure-constraints and profit maximization in U.S. agriculture. American Journal of Agricultural Economics 68, 857–865.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Review of Economic Studies 70 (2), 317–341.

Marschak, J., Andrews, W., 1944. Random simultaneous equations and the theory of production. Econometrica 12 (3-4), 143–205.

McFadden, D., 1978. Cost, revenue, and profit function. In: Fuss, M., McFadden, D. (Eds.), Production Economics: A Dual Approach to Theory and Applications. Amsterdam: North-Holland Publishing Co.

Olley, G. S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297.

Shephard, R., 1974. Indirect production functions. Verlag Anton Hain, Meisenheim Am Glad.

Van Biesebroeck, J., 2005. Firm size matters: Growth and productivity growth in African manufacturing. Economic Development and Cultural Change 53 (3), 545–583.

Varian, H., 1984. The nonparametric approach to production analysis. Econometrica 52 (3), 579–598.

Varian, H., 1990. Goodness-of-fit in optimizing models. Journal of Econometrics 46 (1-2), 125–140.

Whited, T. M., Wu, G., 2006. Financial constraints risk. Review of Financial Studies 19, 531–559.

Wooldridge, J., 2009. On estimating firm-level production functions using proxy variables to control for unobservables. Economics Letters 104 (112-114).

Figure 1: Profit maximization without heterogeneity in productivity

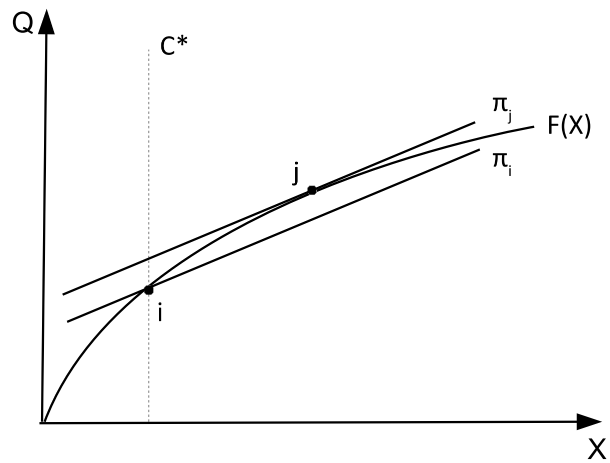

Figure 2: Production functions with heterogeneity in productivity

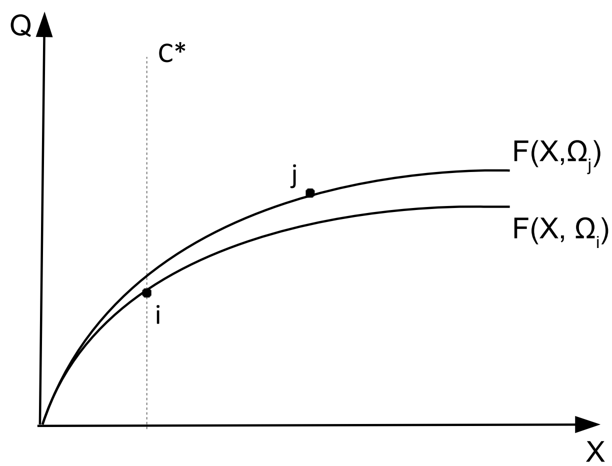

Figure 3: Financial constraints over time

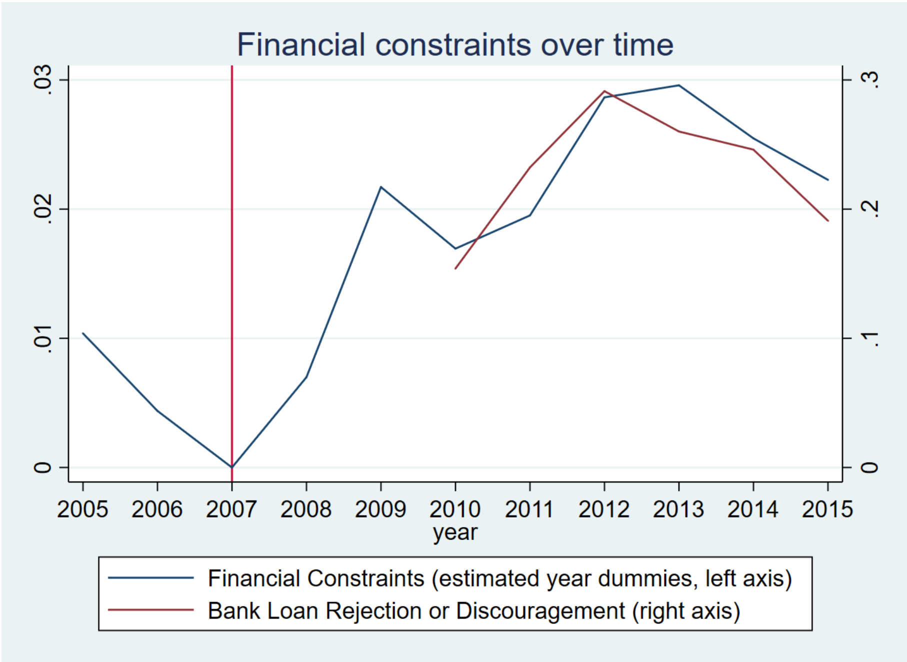

Figure 4: Financial constraints by country over time

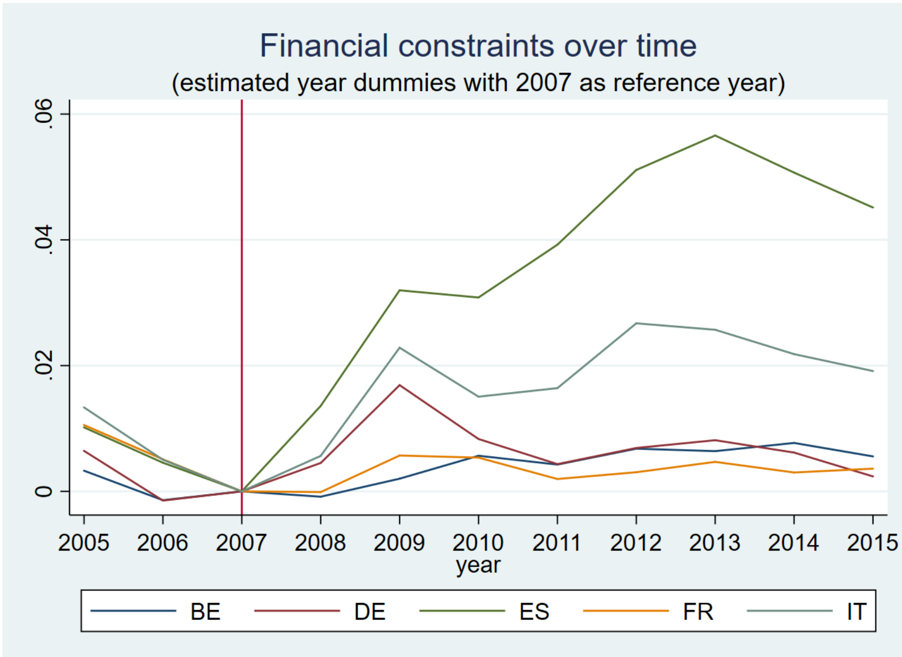

Table 1: Variable definition and data source

VARIABLE	DEFINITION	AVAILABLE FOR	SOURCE
Deflated revenue$_{it}$	Annual sales revenue in million 2008 EUR		Orbis Europe
P_{it}	Output deflator		EU KLEMS and eurostat
$W_{L,it}$	Labor cost divided by number of employees in FTE		Orbis Europe
$W_{C,it}$	Capital deflator		EU KLEMS and eurostat
$W_{M,it}$	Output deflator		EU KLEMS and eurostat
Labor$_{it}$	Number of employees in FTE		Orbis Europe
Deflated capital$_{it}$	Deflated total tangible fixed assets in million 2008 EUR		Orbis Europe
Deflated materials$_{it}$	Deflated material costs in million 2008 EUR		Orbis Europe
Productivity$_{it}$	Natural log of estimated latent input; $log(\hat{\Omega}_{it})$		Own Calculations
Financial Constraints$_{it}$	Foregone profitability due to financial constraints; FC_{it}		Own Calculations
Most pressing problem$_{it}$	Dummy equal to 1 when a firm perceives this problem to be its most pressing problem, and 0 ohterwise	Access to finance, Finding customers, Competition, Costs of production or labor, Availability of skilled staff, Regulation	SAFE (Q0)
Rejection or discouragement$_{it}$	Dummy equal to 1 when a firm did not apply for this source of external financing out of fear of rejection or when a firm applied for it and either got rejected or refused the offer because the borrowing costs (interest rate + fees) were too high; and 0 when a firm applied for this source of external financing and got approved (either in full or partly)	Bank Loan, Credit Line, Trade Credit, Other Financing	SAFE (Q7a, Q7b)
Rejection$_{it}$	Dummy equal to 1 when a firm applied for this source of external financing and either got rejected or refused the offer because the borrowing costs (interest rate + fees) were too high; and 0 when a firm applied for this source of external financing and got approved (either in full or partly)	Bank Loan, Credit Line, Trade Credit, Other Financing	SAFE (Q7a, Q7b)
Obstacle$_{it}$	Dummy equal to 1 when a firm did not apply this source of external financing out of fear of rejection or when a firm applied for it and either got rejected or refused the offer because the borrowing costs (interest rate + fees) were too high; and 0 when a firm applied for this source of external financing and got approved (either in full or partly) or did not apply for this source of external financing because it had sufficient internal funds available	Bank Loan, Credit Line, Trade Credit, Other Financing	SAFE (Q7a, Q7b)
Financial pressure$_{it}$	Ratio of total interest payments to EBIT		Orbis Europe
Leverage$_{it}$	Ratio of total liabilities (net of cash and cash equivalents) to total assets		Orbis Europe
Total assets$_{it}$	Total assets in million 2010 EUR		Orbis Europe
Age$_{it}$	Number of years since incorporation		Orbis Europe
Δln(Fixed Assets$_{it}$)	ln(real tangible fixed assets$_{it}$) - ln(real tangible fixed assets$_{it-1}$)		Orbis Europe
Δln(Employees$_{it}$)	ln(number of employees$_{it}$) - ln(number of employees$_{it-1}$)		Orbis Europe
DSO$_{it}$	Days sales outstanding = 365 * accounts receivable$_{it}$ / sales$_{it}$		Orbis Europe
DPO$_{it}$	Days payable outstanding = 365 * accounts payable$_{it}$ / material costs$_{it}$		Orbis Europe

Table 2: Observations included

Country	Firm-year observations	Number of firms
BE	4,604	845
DE	28,132	7,698
ES	183,757	37,768
FR	99,833	24,738
IT	283,452	53,253
Total	599,778	124,302

Table 3: Summary statistics

This table shows summary statistics of all variables used in this paper. Panel A shows all variables used to estimate the production function of the firms and to identify financial constraints. Panel B shows summary statistics for our new measure of financial constraints and three measures that are derived from the firm's replies to the SAFE survey. Panel C shows summary statistics of variables that are typically believed to be related to financial constraints either as determinant or as affected outcome variable.

	Obs.	Mean	St.Dev.	Min.	Max.
Panel A					
Deflated revenue$_{it}$	599,778	16.69	286.2	0.014	63,553
$W_{L,it}$	599,778	0.035	0.013	0.010	0.715
$W_{C,it}$	599,778	0.980	0.059	0.833	1.102
$W_{M,it}$	599,778	0.980	0.059	0.833	1.102
Labor$_{it}$	599,778	57.82	469.2	5.000	71,205
Deflated capital$_{it}$	599,778	3.068	31.75	0.001	6,256
Deflated materials$_{it}$	599,778	9.608	224.2	0.001	52,666
Productivity$_{it}$	599,778	4.121	41.47	0.000	3,093
Panel B					
Financial Constraints$_{it}$	599,778	0.107	0.125	0.000	0.625
Rejection or discouragement:					
Bank Loan$_{it}$	1,986	0.230	0.421	0.000	1.000
Credit Line$_{it}$	1,499	0.271	0.445	0.000	1.000
Trade Credit$_{it}$	1,676	0.181	0.385	0.000	1.000
Other Financing$_{it}$	884	0.204	0.403	0.000	1.000
Most pressing problem:					
Access to finance$_{it}$	5,525	0.121	0.326	0.000	1.000
Finding customers$_{it}$	5,525	0.270	0.444	0.000	1.000
Competition$_{it}$	5,525	0.140	0.347	0.000	1.000
Costs of production or labor$_{it}$	5,525	0.200	0.400	0.000	1.000
Availability of skilled staff$_{it}$	5,525	0.093	0.291	0.000	1.000
Regulation$_{it}$	5,525	0.083	0.275	0.000	1.000
Panel C					
Financial Pressure$_{it}$	599,778	0.526	0.661	0.000	16.77
Leverage$_{it}$	599,778	0.547	0.307	-0.626	1.248
Total Assets$_{it}$	599,777	9.139	31.42	0.092	1,151
Age$_{it}$	599,778	22.48	15.59	1.000	181.0
Δln(Fixed Assets$_{it}$)	423,945	-0.006	0.263	-0.626	1.423
Δln(Employees$_{it}$)	423,945	0.004	0.114	-0.446	0.405
DSO$_{it}$-DPO$_{it}$	423,945	-47.70	105.0	-440.4	197.8

Table 4: The FC measure and firm characteristics

This table shows the Mean and Standard Deviation (between brackets) of our new measure of financial constraints. In addition to results for the whole sample, we show the results per country, for three firm size groups and for three age groups.

	All	Micro	Small	Medium-Large	Young	Mature	Old
All	0.108	0.118	0.112	0.087	0.133	0.108	0.092
	(0.125)	(0.129)	(0.129)	(0.108)	(0.143)	(0.122)	(0.112)
BE	0.059	–	0.060	0.059	0.066	0.062	0.055
	(0.083)		(0.085)	(0.083)	(0.092)	(0.081)	(0.082)
DE	0.099	0.112	0.103	0.098	0.098	0.103	0.096
	(0.117)	(0.123)	(0.120)	(0.116)	(0.119)	(0.116)	(0.116)
FR	0.067	0.069	0.065	0.068	0.074	0.066	0.065
	(0.081)	(0.075)	(0.078)	(0.094)	(0.084)	(0.079)	(0.081)
ES	0.122	0.125	0.123	0.107	0.133	0.124	0.109
	(0.120)	(0.121)	(0.121)	(0.114)	(0.126)	(0.120)	(0.115)
IT	0.117	0.133	0.122	0.084	0.155	0.113	0.095
	(0.140)	(0.150)	(0.145)	(0.106)	(0.163)	(0.137)	(0.120)

Table 5: Relation between the FC measure and self-reported financial constraints

This table tests whether our measure of financial constraints correlates with five measures of financial constraints that are derived from the firms' replies to the SAFE survey. To this end, in Panel A, we regress a dependent variable Y on the new measure of financial constraints. In Panel B, we include in addition country, sector and year fixed effects. In Panel C, we include in addition to Panel B the firms' one year lagged financial pressure (i.e. the inverse of the interest coverage ratio), leverage, age and size. Y is respectively a measure of access to finance being the most pressing problem of a firm in column 1 and different measures of loan rejection or discouragement in columns 2 to 5. The table reports marginal effects of logit regressions. Standard errors are clustered at the firm level. ***, ** and * denote $p<0.01$, $p<0.05$ and $p<0.1$ respectively.

	(1)	(2)	(3)	(4)	(5)
	Most pressing problem:	Rejection or discouragement:			
	Access to Finance$_{it}$	**Bank Loan**$_{it}$	**Credit Line**$_{it}$	**Trade Credit**$_{it}$	**Other Financing**$_{it}$
Panel A					
FC_{it}	0.112***	0.477***	0.304***	0.292***	0.451***
	(0.035)	(0.090)	(0.101)	(0.091)	(0.131)
Pseudo R-squared	0.00219	0.0135	0.00529	0.00670	0.0142
Control variables	No	No	No	No	No
Country FE	No	No	No	No	No
Sector FE	No	No	No	No	No
Year FE	No	No	No	No	No
Panel B					
FC_{it}	0.079**	0.448***	0.353***	0.255***	0.389**
	(0.033)	(0.097)	(0.116)	(0.094)	(0.158)
Pseudo R-squared	0.0643	0.126	0.0993	0.112	0.143
Control variables	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Panel C					
FC_{it}	0.044	0.403***	0.260**	0.194**	0.314*
	(0.034)	(0.102)	(0.126)	(0.098)	(0.168)
Observations	5,195	1,785	1,348	1,398	716
Pseudo R-squared	0.137	0.169	0.146	0.143	0.166
Control variables	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 6: Determinants of Financial Constraints

This table tests whether our measure of financial constraints (FC) correlates with variables that are typically believed to be determinants of financial constraints. To this end, we regress a dependent variable Y on the firms' one year lagged financial pressure (i.e. the inverse of the interest coverage ratio), leverage, age and size. Y is respectively our FC measure in column 1, a measure of access to finance being the most pressing problem of a firm in column 2 and different measures of loan rejection or discouragement in columns 3 to 6. As our new financial constraints measure is continuous, column 1 reports OLS coefficients. The table reports marginal effects of logit regressions in columns 2 to 6. Standard errors are clustered at the firm level. ***, ** and * denote $p<0.01$, $p<0.05$ and $p<0.1$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Most pressing problem:	Rejection or discouragement:			
	FC$_{it}$	**Access to Finance**$_{it}$	**Bank Loan**$_{it}$	**Credit Line**$_{it}$	**Trade Credit**$_{it}$	**Other Financing**$_{it}$
Financial Pressure$_{it-1}$	0.013***	0.025***	0.048***	0.088***	0.045***	0.034
	(0.000)	(0.004)	(0.012)	(0.027)	(0.014)	(0.022)
Leverage$_{it-1}$	0.005***	0.230***	0.358***	0.453***	0.242***	0.246***
	(0.001)	(0.010)	(0.059)	(0.077)	(0.055)	(0.083)
ln(age)$_{it-1}$	-0.001***	-0.001	-0.037**	0.010	-0.021	0.038
	(0.000)	(0.006)	(0.016)	(0.021)	(0.015)	(0.024)
ln(total assets)$_{it-1}$	-0.029***	-0.002	-0.010	-0.022**	-0.008	-0.032*
	(0.000)	(0.003)	(0.009)	(0.010)	(0.009)	(0.017)
Observations	599,778	5,195	1,785	1,348	1,398	716
(Pseudo) R-squared	0.188	0.137	0.161	0.144	0.141	0.159
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Financial constraints and non-financial constraints

This table tests whether our measure of financial constraints correlates with non-financial issues that are replied to the SAFE survey by firms to be most pressing. To this end, in Panel A, we regress a dependent variable Y on the new measure of financial constraints. In Panel B, we include in addition country, sector and year fixed effects. In Panel C, we include in addition to Panel B the firms' one year lagged financial pressure (i.e. the inverse of the interest coverage ratio), leverage, age and size. Y is respectively a dummy that indicates as respective most pressing problem: finding customers, competition, cost of production or labor, availability of skilled staff and regulation. The table reports marginal effects of logit regressions. Standard errors are clustered at the firm level. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	The firm perceives the following as its most pressing problem:				
	(1)	(2)	(3)	(4)	(5)
	Finding customers$_{it}$	**Competition**$_{it}$	**Costs of production or labor**$_{it}$	**Availability of skilled staff**$_{it}$	**Regulation**$_{it}$
Panel A					
FC_{it}	0.025	-0.075*	-0.022	-0.074*	-0.073*
	(0.052)	(0.045)	(0.049)	(0.039)	(0.040)
Pseudo R-squared	3.55e-05	0.000684	3.86e-05	0.00111	0.00132
Control variables	No	No	No	No	No
Country FE	No	No	No	No	No
Sector FE	No	No	No	No	No
Year FE	No	No	No	No	No
Panel B					
FC_{it}	0.036	-0.078*	-0.012	-0.013	-0.041
	(0.056)	(0.046)	(0.050)	(0.036)	(0.031)
Pseudo R-squared	0.0447	0.0457	0.0491	0.0930	0.107
Control variables	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
PanelC					
FC_{it}	0.054	-0.054	-0.000	-0.017	-0.039
	(0.058)	(0.047)	(0.053)	(0.036)	(0.031)
Observations	5,438	5,238	5,328	4,998	5,029
Pseudo R-squared	0.0493	0.0488	0.0502	0.0998	0.118
Control variables	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 8: The FC measure and real effects

This table tests whether our measure of financial constraints (FC) correlates with variables related to firm growth and the trade credit channel. All columns report OLS coefficients. Standard errors are clustered at the firm level. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δln(Fixed Assets$_{it}$)		**Δln(Employees$_{it}$)**		**DSO$_{it}$-DPO$_{it}$**	
Foregone Profitability$_{it-1}$	-0.111***	-0.065***	-0.085***	-0.108***	-12.450***	-8.122***
	(0.004)	(0.007)	(0.002)	(0.003)	(0.968)	(1.630)
ln(Fixed Assets$_{it-1}$)	-0.001***	-0.255***				
	(0.000)	(0.002)				
ln(Employees$_{it-1}$)			-0.007***	-0.331***		
			(0.000)	(0.002)		
DSO$_{it-1}$-DPO$_{it-1}$					0.785***	0.257***
					(0.001)	(0.003)
ln(Acc. Payable$_{it-1}$)						
ln(Acc. Receivable$_{it-1}$)						
Financial Pressure$_{it-1}$		-0.017***		-0.008***		-0.585***
		(0.001)		(0.000)		(0.184)
Leverage$_{it-1}$		-0.075***		-0.015***		-9.804***
		(0.004)		(0.002)		(0.890)
ln(age)$_{it-1}$		-0.060***		0.001		-5.425***
		(0.004)		(0.002)		(0.988)
ln(total assets)$_{it-1}$		0.133***		0.094***		14.565***
		(0.003)		(0.001)		(0.539)
Observations	423,945	423,945	423,945	423,945	423,945	423,945
R-squared	0.003	0.362	0.010	0.382	0.644	0.781
Country FE	No	Yes	No	Yes	No	Yes
Sector FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Table 9: The FC measure and widely used financial constraints indices

Panel A	FC_{it}	Kaplan-Zingales$_{it}$	Whited-Wu$_{it}$
Kaplan-Zingales$_{it}$	0.057		
Whited-Wu$_{it}$	0.228	0.057	
Hadlock-Pierce$_{it}$	0.155	-0.123	0.686

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B			$\mathbf{FC}_{it}$			
Q_{it}	0.008	0.008				
	(0.006)	(0.012)				
TLTD(kz)$_{it}$	0.019	-0.008				
	(0.012)	(0.016)				
CF(kz)$_{it}$	-0.006**	-0.008***				
	(0.002)	(0.002)				
Div(kz)$_{it}$	-0.113***	-0.054				
	(0.036)	(0.039)				
Cash(kz)$_{it}$	0.002	-0.002				
	(0.001)	(0.002)				
ISG_{st}			0.018	0.020		
			(0.032)	(0.018)		
SG_{it}			-0.015	-0.056***		
			(0.031)	(0.016)		
TLTD(ww)$_{it}$			-0.011	0.020		
			(0.030)	(0.031)		
CF(ww)$_{it}$			-0.234***	-0.234***		
			(0.049)	(0.043)		
Div(ww)$_{it}$			0.003	-0.005		
			(0.008)	(0.009)		
Size$_{it}$			-0.014***	-0.021*		
			(0.002)	(0.012)		
Size(hp)$_{it}$					0.033**	-0.010
					(0.013)	(0.046)
Size(hp)$^2_{it}$					-0.005***	-0.002
					(0.001)	(0.005)
Age(hp)$_{it}$					0.000	-0.003
					(0.000)	(0.002)
Observations	1,045	1,045	1,045	1,045	1,045	1,045
R-squared	0.028	0.858	0.079	0.868	0.056	0.854
Country FE	No	Yes	No	Yes	No	Yes
Sector FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes
Index	Kaplan-Zingales		Whited-Wu		Hadlock-Pierce	

Appendix A: Operationalization of the identification of productivity

Definitions and characterization. We first define (OP)-rationalizability of the dataset S under financial constraints:

Definition 1. *The dataset S is (OP)-rationalizable under financial constraints if there exist latent input levels Ω_i and a production function F such that, for all firm observations $i \in N$,*

$$(\mathbf{X}_i, \Omega_i) \in \arg\max_{\mathbf{X},\Omega} P_i Q_i - \mathbf{W}_i \mathbf{X}_i - \Omega_i \ \textit{s.t.}\ \mathbf{W}\mathbf{X} \leq C.$$

From Theorem 3 of Varian (1984), we can define the following testable implications for (OP)-rationalizability of a given dataset S.[17]

Proposition 1. *Let $S = \{\mathbf{W}_i, \mathbf{X}_i, P_i, Q_i\}_{i \in N}$. The following statements are equivalent:*

(i) The dataset S is (OP)-rationalizable under financial constraints;

(ii) There exist latent input numbers $\{\Omega_i\}_{i \in N} > 0$ that satisfy, for all $i \in N$ and j in $\boldsymbol{T}_i^{FC} = \{j | C \geq \mathbf{W}_i \mathbf{X}_j\}$, the inequalities

$$\forall i \in \{1, \ldots, N\} : P_i Q_i - \mathbf{W}_i \mathbf{X}_i - \Omega_i \geq P_i Q_j - \mathbf{W}_i \mathbf{X}_j - \Omega_j.$$

[17] Theorem 3 of Varian (1984) did not explicitly consider financial constraints or latent input. However, these extensions of Varian's original result are fairly straightforward and, therefore, we do not include an explicit proof.

Operationalization We can use linear programming to check our testable conditions for (OP)-rationalization under financial constraints. The linear programming problem minimizes the sum $\sum_i(\Omega_i)$ subject to the rationalizability constraints in condition (ii) of Proposition 1.

To operationalize these conditions for each firm observation $i \in N$, we need to empirically approximate the set $\boldsymbol{T}_i^{FC}$. Here, we use that firm i's observed cost $\mathbf{W}_i\mathbf{X}_i \leq C$. Then, we can define the set $\hat{\boldsymbol{T}}_i^{FC} = \{j|\mathbf{W}_i\mathbf{X}_i \geq \mathbf{W}_i\mathbf{X}_j\}$, which contains all firm observations j with associated cost $\mathbf{W}_i\mathbf{X}_j \leq \mathbf{W}_i\mathbf{X}_i$. By construction we have that $\hat{\boldsymbol{T}}_i^{FC} \in \boldsymbol{T}_i^{FC}$. Thus, we implicitly set C equal to $\mathbf{W}_i\mathbf{X}_i$.

To control for heterogeneity that cannot be considered as latent input (e.g., measurement error, deviations from optimal conduct), we account for (small) deviations form "*exactly*" optimizing behavior in practice by using a goodness-of-fit parameter σ.[18] Basically, it weakens the original rationalizability requirement in Proposition 1 by lowering the right hand sides of the inequality constraints in condition (ii).[19] Using this goodness-of-fit parameter considers "close-to" (instead of "exactly") (OP)-rationalizable firm behavior. In our following empirical application, we will set $\sigma = 0.9$.

[18] We may need to account for such deviations in practice as observed firm behavior may effectively fail the "exact" rationalizability condition in Proposition 1. Specifically, assume that, for some j and i, $P_iQ_i - \mathbf{W}_i\mathbf{X}_i < P_iQ_j - \mathbf{W}_i\mathbf{X}_j$ and $P_jQ_j - \mathbf{W}_j\mathbf{X}_j < P_jQ_i - \mathbf{W}_j\mathbf{X}_i$. Then, we must have $\Omega_j > \Omega_i$ (because of the first inequality) and $\Omega_i > \Omega_j$ (because of the second inequality), which is infeasible. Actually, we can give this infeasibility an intuitive interpretation. The two inequalities above imply that *both* firm observation j and firm observation i turn out to be profit inefficient when compared to each other (under their respective prices). Clearly, we cannot rationalize such behavior as profit efficient with a single dimension of heterogeneity in production (i.e. a single latent input). From all this, it is clear that infeasibilities will occur only for severe violations of profit maximization (when ignoring heterogeneity in productivity). Also, feasibility is guaranteed if all firm observations face the same prices.

[19] See, for example, Afriat (1972) and Varian (1990) for alternative goodness-of-fit measures that have been used in nonparametric production analysis.

Taken together, we obtain the following linear program:

$$\min_{\Omega_i \in \mathbb{R}_+} \sum_i \frac{\Omega_i}{\mathbf{W}_i \mathbf{X}_i}$$

$$\text{s.t.}$$

$$\forall i \in \{1, \ldots, N\} : P_i Q_i - \mathbf{W}_i \mathbf{X}_i - \Omega_i \geq \sigma P_i Q_j - (\mathbf{W}_i \mathbf{X}_j)/\sigma - \Omega_j \text{ for all } j \in \hat{\boldsymbol{T}}_i^{FC},$$

$$\text{with } \hat{\boldsymbol{T}}_i^{FC} = \{j | \mathbf{W}_i \mathbf{X}_i \geq \mathbf{W}_i \mathbf{X}_j\}.$$

This program obtains estimates of the unobserved Ω_i that we will use in our practical implementation. We set $\theta = 0.9$, which is the most adequate choice for datasets that may be characterized by considerable noise (see Cherchye et al. (2018)).

Appendix B: Additional tables

Table 10: Relation between the FC measure and self-reported financial constraints

This table tests whether our measure of financial constraints correlates with five measures of financial constraints that are derived from the firms' replies to the SAFE survey. To this end, in Panel A, we regress a dependent variable Y on the new measure of financial constraints. In Panel B, we include in addition country, sector and year fixed effects. In Panel C, we include in addition to Panel B the firms' one year lagged financial pressure (i.e. the inverse of the interest coverage ratio), leverage, age and size. Y is respectively a measure of access to finance being the most pressing problem of a firm in column 1 and different measures of loan rejection or discouragement in columns 2 to 5. The table reports marginal effects of logit regressions. Standard errors are clustered at the firm level. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rejection:				Obstacle:			
	Bank Loan$_{it}$	**Credit Line**$_{it}$	**Trade Credit**$_{it}$	**Other Financing**$_{it}$	**Bank Loan**$_{it}$	**Credit Line**$_{it}$	**Trade Credit**$_{it}$	**Other Financing**$_{it}$
Panel A								
FC$_{it}$	0.409***	0.266***	0.198**	0.391***	0.121***	0.111***	0.075***	0.078***
	(0.084)	(0.099)	(0.094)	(0.143)	(0.030)	(0.029)	(0.028)	(0.022)
R-squared	0.015	0.005	0.004	0.014	0.004	0.004	0.003	0.007
Control vars	No	No	No	No	No	No	No	No
Country FE	No	No	No	No	No	No	No	No
Sector FE	No	No	No	No	No	No	No	No
Year FE	No	No	No	No	No	No	No	No
Panel B								
FC$_{it}$	0.331***	0.293**	0.168*	0.214	0.086***	0.086***	0.052**	0.067***
	(0.080)	(0.115)	(0.093)	(0.134)	(0.029)	(0.025)	(0.023)	(0.019)
R-squared	0.153	0.104	0.099	0.191	0.075	0.076	0.085	0.070
Control vars	No	No	No	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C								
FC$_{it}$	0.325***	0.222*	0.184*	0.221	0.060**	0.048**	0.042*	0.065***
	(0.084)	(0.123)	(0.097)	(0.148)	(0.027)	(0.023)	(0.022)	(0.020)
Pseudo R-squared	0.189	0.144	0.135	0.209	0.129	0.151	0.129	0.101
Observations	1,564	1,125	1,180	511	4,874	4,783	4,565	4,111
Control vars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes