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Financial Constraints, Productivity, and Investment

Evidence from Lithuania

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Financial Constraints, Productivity, and Investment: Evidence from Lithuania
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ABSTRACT: This paper studies the relation between firms' access to finance, labor productivity and investment using Lithuanian firm-level data from 2000–2018. To do so, we construct a measure of financial constraints. We estimate that, given firm characteristics, removing these constraints can improve average productivity and investment of firms in Lithuania by 0.51 percent and 7.2 percent, respectively. Our results further suggest that policies targeting firm age and size together will be more effective in mitigating the impact of financial constraints as the relationship between firm age and size with financial constraints exhibits non-linearities.

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WORKING PAPERS

Financial Constraints, Productivity, and Investment

Evidence from Lithuania

Prepared by Karim Foda, Yu Shi, and Maryam Vaziri[1]

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Contents

1. Introduction

Do financial constraints limit firms' investment and productivity growth, and if so, how could policies help in improving firm access to finance? These questions have been of great interests to researchers and policymakers for a long time. Seminal work by Rajan and Zingales (1996) showed that the lower cost of access to external financing in countries with a more developed financial sector, facilitates economic growth. Since then, a large body of literature has been further exploring the implications of financial frictions on economic outcomes. In recent years, and with the growing availability of micro-data, studies have taken a firm-level approach to answer this question.

Building on this growing literature, we use administrative firm-level data from Lithuania during the period of 2000–2018 and investigate the relationship of access to finance with productivity and investment. Lithuania provides an appealing setup for answering our research question as a converging economy with a developing financial system. Policy makers and firm-level surveys often cite access to finance as a barrier to growth, but they do not adequately distinguish between productive firms that lack the ability to invest and less viable firms. With administrative data on the universe of firms in Lithuania, we utilize information on both firm assets and liabilities to better assess if access to finance is indeed a barrier for a wide range of firms which differ in their ability and desire to invest. Our data is superior to most alternative firm-level datasets given the high coverage of micro and small firms. This analysis provides a more complete picture on firm access to finance and its impact on economic growth in Lithuania. It also helps guide policymakers on how to target efforts to improve the allocation of capital to productive firms that drive growth and support sustained economic convergence.

One empirical challenge in the literature is in constructing a clean measure of unobserved firm financial constraints. Studies often focus on a single given financial variable (such as debt-to-asset ratios or cash holdings, etc.) to imply the difficulty or ease of access to finance. However, these financial variables are often chosen optimally by the firm, and therefore do not accurately reflect the extent to which a firm might be financially constrained. For example, high levels of cash holding at first glance might suggest that firms have excess resources, while in reality some firms may be hoarding cash as they lack access to external sources of financing. Theoretically, a good measure of a firm's degree of financial constraint should uncover the gaps between existing and desired levels of financing for investment. In other words, it should contain information on both firms' ability and their desire to finance investments. To this end and motivated by the approach of Pal and Ferrando (2010) and Ferrando and Ruggieri (2018), we use information from both the liability and the asset side of firm balance sheets and classify firms into two groups of constrained and unconstrained. In this categorization we combine multiple financial variables, rather than focusing on just one variable to understand the financial state of the firm. By gathering information on firms' investment, cash holdings and changes in debt and considering them all together rather than in isolation, we are better able to capture the financial state of the firm and its desire to invest (see Section 4.1 for more details). Next, to transform the binary classification into a continuous index, we estimate an ordered probit regression of the dummy of constrained on firm characteristics, including size, age, cash holdings, and debt-to-asset ratios. We take the predicted probability estimated by this regression as our index of financial constraints. This index improves the identification issue to some extent, as it contains information on various financial variables, and allows for non-linear relationships between observed financial variables and the unobserved constraints.

To study the relationship between firm access to finance and productivity and in- vestment, we regress investment and firm-level labor productivity measured as value added per employee) characteristics on the continuous index of financial constraints. In the baseline specification, we control for other firm characteristics together with firm and time-sector fixed effects. The results (see Section 4 for more details) show that our index is significant in predicting firm labor productivity and investment after controlling for financial variables. This further supports our argument that the continuous index is superior to the standard approach by just controlling for firm financial variables.

Our main findings are as follows. First, as expected we find that more constrained companies on average show lower investment and productivity. The relationship is both economically and statistically significant. Using a back-of-the-envelope calculation, we find that given firm characteristics, removing financial constraints increases average firm labor productivity and investment by roughly 0.51 percent and 7.2 percent respectively. Second, our results show that age and size together contain important information in predicting the probability of firms' financing constraints and that the relationship between the two variables is non-linear. More specifically, among young firms, large firms have a higher predicted probability of being constrained and the relationship with size reverses as firms age increase (among older firms, smaller firms are more likely to be constrained). This result is intuitive since our measure of financing constraint captures both the desire and the ability of firms to borrow. Large but young firms that have high growth potential may not be able to access sufficient amount of external financing to reach their desired size right away.[2]

Our findings have important policy implications. We show that in a converging economy like Lithuania with already high growth and rapid financial deepening improving access to finance to a select group of firms could further boost productivity and investment growth. In the case of Lithuania, one main group is young and large firms with a high potential for further growth. For example, removing firm financial constraints that were in place in 2018 would still improve average labor productivity and investment by 0.47 percent and 6.7 percent, respectively. In addition, we propose both firm size and age as key parameters for capital deepening policies. In line with Hadlock and Pierce (2010), firm size and age are easily observable and not subject to possible specification errors in a model-based measure of financial constraint. We show that the two variables combined predict well financial constraints facing individual firms. Therefore, including both firm size and age will help policies to better target firms in greater need of external financing while minimizing the administrative burdens.

1.1 Literature Review

This paper relates to studies exploring the relationship between access to financing and impact on growth and investment (Cooley and Quadrini, 2001; Albuquerque and Hopenhayn, 2004; Clementi and Hopenhayn, 2006; Caggese and Cunat, 2013; Buera and Karmakar, 2017; Vaziri, 2021; Ferreira et al., 2021). Empirically, a strand

[2] This could be driven by relationship lending Elyasiani and Goldberg (2004) or having a large share of intangible and uncollateralised assets on the balance sheet.

of the literature has investigated the extent to which the degree of financial development in a country has facilitated growth (Rajan and Zingales, 1996). lore recent studies use firm- level data to measure the effect of financial constraints on economic performance (Chen and Guariglia, 2013; Ferrando and Ruggieri, 2018; lanaresi and Pierri, 2019; Cevik and liryugin, 2022).

A challenge faced by the empirical literature is the measurement of access to financing. A common method in measuring these constraints is using firms' balance sheet information such as cash holdings or firm's leverage (Chen and Guariglia, 2013; Gomis and Khatiwada, 2017; Levine and Warusawitharana, 2021). However, taking cash holding as an example, it is an endogenous financial choice it is not immediately clear if this variable would always correlate with better access to liquidity. For example, it is possible that firms decide to increase their cash holdings if they do not have access to alternative financing methods. Alternatively, studies have used survey data or exploited exogenous shocks to banks and impact on firms using data on bank to firm linkages (e.g., Buera and Karmakar 2017)). These methods while providing a more exogenous measure, either require data that is not easily available or only cover a smaller subset of firms. To overcome these challenges, we follow the methodology of Ferrando and Ruggieri (2018) combining information from a set of balance sheet variables to mitigate the endogeneity issues without increasing the data requirements. Ferrando and Ruggieri (2018) use Orbis dataset and do a cross-country analysis of Euro area firms finding that financing constraints negatively affect firms' productivity especially in countries with lower degrees of financial development. With respect to their work, our data set provides a better coverage of young and SME firms. Therefore, the administrative data allows us to further explore the effect of financing constraints on firms' observable characteristics.

Our paper also contributes to the literature studying the effect of financial constraints on transition and emerging economies. In this respect Gatti and Love (2008) use survey data to study the Bulgarian economy and find that access to credit is positively associate with an improvement in productivity. Chen and Guariglia (2013) study the Chinese manufacturing sector and find that an increase in access to internal finance, measured by cash flow, is associated with an improvement in total factor productivity. To the best of our knowledge, our paper provides the most comprehensive analysis of the impact of financial constraints in the context of transition economies.

Our paper also adds to the discussions around the role of policy in alleviating the impact of financial frictions on firms. Hadlock and Pierce (2010) provide a detailed discussion on validity of various measures of financial constraints collecting detailed qualitative information from firms' financial filings and combining it with the balance sheet of publicly listed firms in the US using Compustat. They find that age and size have a high prediction power for the level of financial constraints and the effect of these constraints dampens as firms mature and grow.[3] Similar to Hadlock and Pierce (2010) our results highlight the importance of firm age and size, however, we also uncover further nonlinearities in this respect. In particular we find that among young firms, larger firms have a higher probability of being constrained while the relationship reverses for older firms. This could be explained by large young firms having a higher propensity to grow even further as they are most likely the very productive firms of the sample. Therefore, our results suggest that by combining information from firms' age and size, it is possible to target firms more effectively.

[3] Note that in the case of Hadlock and Pierce (2010) age refers to the number of years since the firm has become publicly listed.

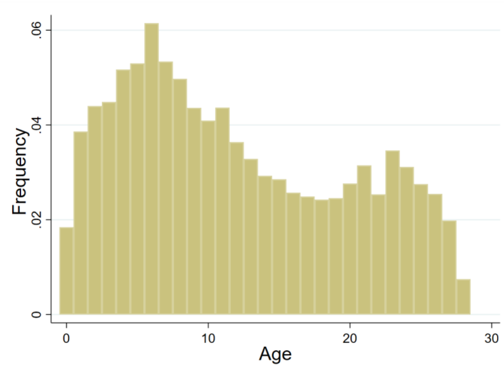
2. Data

The dataset we use to carry out the analysis covers the entire population of active firms in Lithuania from 2000 to 2018.[4] The only excluded firms from our dataset are sole proprietorships or associations (unlimited liability business forms) and public firms. Additionally, the dataset does not include firms in the financial sector, insurance services and public administration. This limitation in particular affects the education and health sector as the majority of bodies in these sectors are public thus leading to an under- representation. A similar concern exists for the agriculture sector in which most firms are sole proprietorships or associations.[5] The dataset further excludes observations that may lead to a violation of data confidentiality requirements.[6] Despite these shortcomings, there is a coverage of close to 95 percent of active firms in Lithuanian economy (Constantinescu and Proskute, 2019).

The dataset provides detailed information on firms' characteristics, balance-sheet, and income statement variables, as well as data on production inputs among others. To carry out our analysis, we first correct for inputting errors and drop firms with negative sales, assets below five thousand euros and firms whose maximum employment never exceeds two over their lifetime.[7] After performing this filtering, we end up with 669,820 unique observations and 86,209 unique firms.

Table 1 reports the coverage of our sample across different sectors. lost firms be- long to Retail Trade and Services followed by the Manufacturing sectors. Firms in the Manufacturing sector are on average larger, both in terms of employment and their asset holdings, with firms in the low-skilled service sector on average including smaller firms. Small and Medium sized Enterprises[8] present the majority of our sample and including between 96–99 percent of firms across different sectors.

Figure 1: Share of Firms in Any Age Cohort in Year 2018



Note: Frequency refers to share among total firms in the sample.

[4] The administrative dataset does not have 2019 data available for all firms, therefore we focus on the period between 2000 and 2018 in our analysis.

[5] For more details refer to Constantinescu and Proskute (2019). For trends on employment and productivity and reallocation of resources during the financial crisis refer to Tarasonis et al. (2021).

[6] This affects very few large firms in Lithuanian economy.

[7] This is to make sure we are capturing active corporations and not individuals who may be benefiting from corporate tax schemes.

[8] The analysis in the table also includes the Micro firms with less than 10 employees.

One advantage of our dataset is its comprehensive coverage of young and small firms.[9] Table 1 depicts the share of firms of any age cohort in 2018. It is worth noting that Lithuania is a transition economy with a young firm population where firms' average age during the period of study is slightly over nine years. In particular, the change in the structure of Lithuanian economy in 1990 implies that the oldest firms in the sample will be at the age 29 in 2019. To further highlight the compositional changes of transition economies as it matures, it is worth noting that during the period of our study the firm's average age increases from 4.6 to 12.6 years. To calculate firm age, we use the variable Register Date when available. If the value is missing for Register Date, we use the first year that a firm appears in the data. Figure 2 and Figure 3 in the appendix depict firms' age distribution in year 2000 and 2018 respectively and capture the maturing of the Lithuanian economy. Figure 4 and 5 show developments of the distribution based on firm size.

Table 1: Share of Firms in Any Age Cohort in Year 2018

Sectors	Manufacturing	IT	Transport	Retail	Services High Skilled[1]	Services Low Skilled[2]	Other[3]
Observation	88,859	23,826	67,163	213,418	88,592	60,513	90,030
Firms	12,486	3,634	9,991	30,256	13,434	11,074	14,796
Employees							
Mean	44.1	18.2	25.4	16.3	11.4	22.6	27.5
Medium	13	6	7	6	5	8	9
Std. dev	131.2	18.2	236.2	159.4	35.3	79.9	99.0
Assets[4]							
Mean	7.6	7.0	7.4	7.4	6.6	6.7	7.5
Median	7.4	6.8	7.3	7.3	6.4	6.4	7.3
Std. dev	1.9	1.7	1.6	1.6	1.6	1.7	1.8
Small	35,632	5,905	19,646	55,953	19,939	20,792	31,103
Medium	13,799	1,281	4,278	8,479	2,570	3,834	9,816
Large	2,669	168	720	885	217	688	1,142
Age	9.7	8.6	8.5	9.1	8.5	8.3	8.4

[1] High skilled service sectors include education, entertainment, health, and professional services.

[2] Low skilled services include hotels, restaurants, support services and other services.

[3] The final column, Other, contains agriculture, mining, electricity, construction, and utilities. Assets are presented as log of total
real assets of firms. SME includes all firms below 250 employees and thus includes micro firms.

[4] Assets are presented as log of total real assets of firms.

Notes: SME includes all firms below 250 employees and thus includes micro-firms. Figures 2 and 3 show the age distribution of firms and their development from 2000 to 2018.

[9] In most firm level datasets such as Orbis Bureau van Dijk; young and small firms are often under-represented.

3. Methodology

3.1 Measure of Financial Constraints

Our first step is to create a clean measure of financial constraints. The challenge, how- ever, is that these constraints are not empirically observable in the firms' balance sheets. Additionally, financial decisions of firms themselves are endogenous and are not indicative of whether the firm is constrained or not. Further, methods that exogenously capture the financial conditions of the firm often have high data requirements which are not readily available (for example Campello et al. (2010) use survey data, and Buera and Karmakar (2017) and Chodorow-Reich (2014) use credit registry data to create an exogenous shock based on firm to bank relationships).

To overcome these problems, we create a measure of financial constraint from firms' balance sheet data using information on the asset-side and the liability-side of the balance sheet. Motivated by Ferrando and Ruggieri (2018) and Pal and Ferrando (2010) we classify firms into groups with various degrees of financial constraint. The advantage of this method is that by creating a number of scenarios we can capture both the desire and the ability of firms to invest and thus overcome the common endogeneity problems associated with choosing a single indicator for deciding the extent of financial constraint. A further advantage of this method is its relatively low data requirements along with flexibly adjusting to any data set with balance sheet information. A disadvantage, however, is that it may not be possible to categorize all firms, therefore, leading to a smaller sample size.[10]

Table 2: Classification Scheme

Case	Category	Financial Gap	Δ Debt	investment	other
Case I	U	cash ≥ investment	> 0	>0	$\frac{investment}{L.asset} > -\bar{c_1}$
Case II	U	cash ≥ investment	> 0	<0	
Case III	C	cash < investment	> 0	>0	
Case IV	C	cash < investment	< 0	>0	Debt quartile > $\bar{c_2}$
Case V	C		<0	<0	$\frac{investment}{L.asset} < -\bar{\bar{c_3}}$

Table 2 contains the classification scheme considering five distinct scenarios (I - V) and categorizing firms into two different groups of constrained and unconstrained indicated by C and U respectively. Financial

[10] To mitigate this problem, we use the information from the classification scheme to estimate an ordered probit model. The estimated probit model can be used to create a measure of financial constraint for firms that remain out of the sample; thus, improving coverage. Results remain robust to excluding these firms and solely focusing on classified firms.

gap is defined as fixed investment minus cash flow. For example, case I refers to firms that are investing (desire to invest) and have cash holdings above their investment choice while increasing their debt from the previous years (ability to invest). Case II includes firms who are disinvesting, but they have positive cash holdings and are able to increase their debt. Thus, these firms while having the ability to invest do not have the desire of doing so. The final condition indicated under "other" limits the extent of liquidation of assets by a threshold $\bar{c_1}$ and thus ensures that financial decisions of firms are driven by holding above optimal assets rather than financial problems.

Cases III to V represent firms that are financially constrained relative to cases I and II. In case III firms' internal sources financing is not sufficient therefore they depend on external sources thus making these firms relatively more constrained compared to previous cases. In cases IV and V firms face stronger constraints as they are not even able to increase their debt. In case IV there is an additional condition requiring firms to be on the $\bar{c_2}$ debt quartile thus focusing on the subset of firms that depend on debt as their main source of financing instead of equity, where $\bar{c_2}$ is a given threshold for debt quartile. Next, we assign score 0 to the unconstrained group "U" and score 1 to the constrained group "C".
To test the validity of the classification scheme Figure 6 in the appendix depicts the share of firms categorized as constrained. As expected in years leading to the Global Financial Crisis the share of constrained firms was at its lowest value due to lax lending conditions. Starting from 2009 the tightening of financial conditions is reflected in this share increasing to its highest value. Since the crisis and in the following years the share of constrained firms has declined and stabilized at roughly 55 percent.

Further, financial constraint shows persistence over time. Table 7 presents the transition matrix for the indicator capturing share of firms moving between different categories from one period to the next. Roughly 53 percent of firms that are unconstrained remain un- constrained the next period, while about 47 percent face financial constraint in the following year. As for the constrained firms, there seems to be more persistence with around 71 percent of firms remaining in the same category and roughly 29 percent becoming unconstrained in the subsequent period.

3.2 Empirical Strategy

The previous subsection discussed how firms are classified as financially constrained using information from the asset side and the liability side of the balance sheet. While this classification measure overcomes certain weaknesses of using a single variable to proxy for such constraints e.g., using collateral captures the ability of firms to borrow but not their desire) at its current form it has limited variability on the degree of access to finance. The objective of this subsection is first to create an index of financial constraint using the classification method described in Table 2. Next, this index can be used to estimate the effect of financial constraint on productivity and investment.

To create a continuous index motivated by the approach of Ferrando and Ruggieri (2018), we use the classification scheme described in the previous subsection to estimate an ordered probit regression. In this regard, we run a regression with the classification scheme as the dependent variable controlling for firms' characteristics such as age, size, industry, and financial outcomes. The predicted outcome of the regression can be interpreted as the conditional probability of being financially constrained and will be the index used in the remainder of this paper.

The ordered probit is specified as follows for a given firm i at time t: [11]

$$Pr(I_{i,t} = j) = X_{i,t-1}\mu + c_i + u_{it}, \quad j \in \{0,1\}$$

where $I_{i,t}$ is the classification of firm i at time t according to Table 2. j can take values 0 or 1 with $j = 0$ referring to firms that are categorized as unconstrained, and $j = 1$ shows the constrained group. $X_{i,t-1}$ are firm level characteristics. To account for firm specific characteristics, we include size dummies based on employment for micro, small, medium, and large firms.[12] We also include dummies for age, industry as well as year to control for business cycles. $X_{i,t-1}$ also contains variables on the financial characteristics of firms such as leverage, cash holdings and their interaction with firm size and firm age. All variables relating to firm specific characteristics are lagged one period to avoid simultaneity. Finally, c_i controls for possible correlation between unobserved and time invariant characteristics of firms and $X_{i,t-1}$. In doing so we follow Chamberlain (1979) and take steps similar to Ferrando and Ruggieri (2018). The outcome is reported in the next section.

We then use the estimated the model to form the index of financial constraint denoted by FC_{it} in the remainder of the paper. To verify the validity of our measure we make use of interest payment data on firms' balance sheets. This information is only available after 2016, and therefore was not originally used to classify firms into different categories. In particular, we expect firms that face higher interest rates have a higher likelihood of being constrained. To test, we find the median interest rate for each sector and each year and calculate the average index

3.3 Financial Constraints, Labor Productivity, and Investment

Financial constraints affect the ability of a firm to borrow in order to invest, improve its production capacity and increase its productivity. This section studies how these constraints relate to firms' investment and their implications for the firm-level labor productivity.

The measure of labor productivity is calculated as value added of a given firm, deflated, and divided by the number of employees.[13] To understand the response of firm-level productivity to our measure of financial constraints, we run a regression with the natural logarithm of the firm specific labor productivity as the dependent variable, including a vector of controls for firm characteristics denoted by X^{Ch} and a vector of controls for firm's financial characteristics shown by W^{FC}. The main specification is written as:

$$\ln(prod_{i,t}) = \delta_i + \delta_{st} + \beta_0 + \beta_1 FC_{i,t-1} + \beta_2 \ln(prod_{i,t-1}) + \beta^{ch} X^{ch}_{i,t-1} + \beta^{FC} W^{FC}_{i,t-1} + \epsilon_{i,t}$$

[11] We use an ordered probit specification to highlight it is possible to have more than two groups ranked based on the extent of financial constraint. Results are robust to using a logit specification.

[12] Note that the main analysis focused on firms with more than 10 employees; therefore, the micro category is not included in the regressions.

[13] This measure does not account for the intensive margin of labor supply due to changes in hours worked.

where *ln*($prod_{i,t}$) is the natural log of labor productivity of firm *i* and year *t*, the specification includes firm and sector-year fixed effects denoted by δ_i and δ_{st} respectively. Standard errors are clustered the level of fixed effect and all explanatory variables are lagged to reduce simultaneity bias. $W_{i,t-1}^{FC}$ includes debt ratio and cash to sales ratio while X^{ch} contains variables on firm size, firm age, and their interaction with the financial constraint index.

Next, we explore the relationship between financial constraint and firms' decisions to invest.[14]
Investment at time *t* is defined as the change in fixed assets from time *t* + 1 to
time *t* plus depreciation. The main specification is given by:

$$ln\left(investment_{i,t}\right) = \delta_i + \delta_{st} + \beta_0 + \beta_1 FC_{i,t-1} + \beta_2 \ln\left(prod_{i,t-1}\right) + \beta^{ch} X_{i,t-1}^{ch} + \beta^{FC} W_{i,t-1}^{FC} + \nu_{i,t}$$

The specification contains firm and sector-year fixed effects and standard errors are clustered as before.

Note that we include in this equation *ln*($prod_{i,t-1}$) instead of *ln*($investment_{i,t-1}$) on the right hand side to mitigate attenuation biases, as investment usually is quite volatile.[15] The coefficient of interest is β , estimates the association between financial constraints and investment decision of firms.W^{FC}includes debt and cash, and X^{ch} contains information on firm size, firm age, and their interaction with the financial constraint index.[16] Results are discussed in the next section.

[14] To make sure observations with value zero our included in our regression estimates; when applying the log transformation; we add one to each value.

[15] Usually, firms make one big investment at one time and do small adjustments in following years.

[16] Specifications for investment and firm-level productivity both contain variables that are similar to the variables used creating the index of financial constraint *FC*. We check for multicollinearity to make sure this is not affecting our results.

4. Results

The sample we use in order to estimate the implications of financial constraints is con- structed based on Table 2. We set $\bar{c}_1$= 0.2, where $\bar{c}_1$ sets a limit on the extent of asset liquidation for firms to be considered unconstrained. In our analysis we focus on scenarios in which $\bar{c}_2$ = 1 therefore considering the set of firms that are above the first debt quartile in the data. Debt quartiles are defined based on four-digit NACE sectors for every given year, therefore accounting for differences in firms' financing needs across sectors and over time. $\bar{c}_3$= 0.5 specifying the cutoff for liquidation which categorizes firms as constrained and consequently, in an unfavorable financial situation.[17]

The variables we use from the balance-sheet data to capture the financial position of the firm include debt ratio, fixed assets, investment, profits, cash holdings and sale. We drop the top and bottom 1 percent of observations of each of the mentioned variables. Further, we exclude observations with profit to sales ratio of above or below one, negative sales, and investment ratio.[18]

Table 3 provides summary statistics for the selected sample of firms categorized according to Table 2. Since it is not possible to categorize all firms according to the scheme, we only use a subset of firms. We exclude the micro firms[19] from our baseline analysis, however the results are qualitatively robust to their inclusion. Excluding these firms further implies that the mean and median number of employees will be significantly higher compared to the full sample. Further details about our sample are provided in Table 3. In the next subsections we use this sample to create and index for financial constraints and use this index to study the extent to which financial constraints are associated with firm productivity and investment.

4.1 Index for Financial Constraints

Table 4 presents the results. The estimation is based on an ordered probit model using the classification with two outcomes as the explanatory variable. Standard errors are provided in parenthesis and are robust to heteroskedasticity. We report the outcome of the estimation for four different cases, however, the index used throughout the paper is based on the results of column (3) as it has more controls. Columns (1) – (3) exclude health, education, and agriculture sector, as our sample is not representative of the Lithuanian economy for these sectors as discussed in the Data section of this paper. Recall that 0 referred to firms categorized as unconstrained, and 1 to constrained firms. In all three estimations the coefficient on financial leverage is positive and highly significant suggesting that higher debt ratio increases the probability of belonging to the constrained group. On the other hand, the coefficient on the relative cash holding is negative as expected since higher access to liquidity lowers the likelihood of being constrained. In section 4.3 we discuss in details the relationship of age and size to financial constraints.

[17] We include various robustness checks on these values. In particular, we change $\bar{c}_1$ from 0.05 to 0.3 in 0.05 intervals. We do a similar exercise on $\bar{c}_3$ changing its value from 0.40 to 0.80. We also change $\bar{c}_2$ to 2 and 3 capturing the second and third debt quartile. Results remain robust.

[18] Defined as the relative ratio of investment to lag of fixed assets.

[19] Defined as firms with less than 10 employees.

Table 3: Summary Statistics: Constrained and Unconstrained Firms							
	Manufacturing	**IT**	**Transport**	**Retail**	**Services High Skilled**[1]	**Services Low Skilled**	**Other**[2]
Unconstrained							
Observation	10,528	1,843	3,958	14,701	5,396	5,606	10,482
Firms	4,660	716	2,035	6,204	2,287	2,628	4,213
Employees							
Mean	72.3	56.8	85.7	61.4	38.1	53.6	58.2
Median	30	21	22	20	19	21	28
Assets							
Mean	8.9	8.9	9.0	9.0	8.0	7.8	8.9
Median	8.8	8.8	8.8	8.9	7.8	7.6	8.7
Small	7,123	1,448	3,076	12,283	4,609	4,401	7,411
Medium	2,856	355	716	2,129	712	1,021	2,758
Large	549	40	166	289	75	184	313
Age	10.1	10.0	10.4	10.3	9.6	8.9	9.9
Constrained							
Observation	18,401	1,555	9,542	16,628	4,764	6,689	11,808
Firms	4,709	5,42	2,471	5,515	1,881	2,357	3,869
Employees							
Mean	97.7	74.1	78.8	50.4	37.1	57.0	71.7
Median	37	21	24	25	19	22	31
Assets[3]							
Mean	8.6	8.6	8.9	9.0	8.2	8.7	7.5
Median	8.4	8.5	8.8	8.9	8.0	7.5	8.5
Small	10,947	1,125	7,091	13,439	4,078	5,335	7,786
Medium	5,987	353	2,070	2,888	622	1,190	3,516
Large	1,467	77	381	301	64	274	506
Age							
Mean	10.0	10.1	10.5	9.9	9.1	8.7	9.5

[1] High skilled service sectors include education, entertainment, health, and professional services.

[2] The final column, Other, contains agriculture, mining, electricity, construction, and utilities.

[3] Assets are presented as log of total real assets of firms.

Table 4: Index of Financing Constraints

	1)	2)	3)	4)
L.debt ratio	0.850∗∗∗	0.853∗∗∗	0.751∗∗∗	0.532∗∗∗
L.cash/sales	(0.0267)	(0.0267)	(0.0384)	(0.0274)
	-1.983∗∗∗	-1.976∗∗∗	-1.570∗∗∗	-1.029∗∗∗
	(0.103)	(0.103)	(0.199)	(0.120)
L.age group	✓	✓	✓	✓
L.si:ze	✓	✓	✓	✓
L.si:ze× L.age group		✓	✓	✓
L.si:ze × L.debt ratio			✓	✓
L.si:ze × L.cash/sales			✓	✓
L.age group × L.debt ratio			✓	✓
L.age group × L.cash/sales			✓	✓
Obs	77636	77636	77636	107917
∗ p < .10, ∗∗ p < .05, ∗∗∗ p < .01.				

Notes: Standard errors are in parentheses and are robust to heteroskedasticity. The dependent variable is the index created according to table 2. All specifications exclude firms with fewer than 10 employees and specifications (1) -(3) exclude health, education, and agriculture sectors. Time and sector dummies are included for all specifications, and we use Chamberlain (1979) to control for unobserved characteristics. Age groups are defined as 0-5, 6-10, 11-15, 15+ years. Size groups are defined as 10– 49, 50–249, 250+ employees.

4.2 Financial Constraints, Labor Productivity, and Investment

Table 5 presents the relationship between financial constraints, productivity and investment of firms using the specification discussed in the previous section. Table 9 and Table 10 in the appendix include the full regression outcomes for productivity and investment respectively. As expected, financial constraints limit firms' investment and lead to lower productivity. This is in line with findings of Gatti and Love (2008) for Bulgarian firms, and Chen and Guariglia (2013) for Chinese firms.

Table 5: Financial Constraints, Productivity, and Investment

	(1) In (productivity)	(2) In (investment)
L.FC	-0.0585∗∗∗	-0.821∗∗∗
	(0.0203)	(0.0818)

Standard errors in parentheses. ∗ p < .10, ∗∗ p < .05, ∗∗∗ p < .01.
All specifications include time-sector FE and control for financial characteristics (firm debt and cash) and firm unobserved characteristics with firm FE.

Table 5 suggests that the elasticity of natural logarithm of labor productivity to the measure of financial constraints is -0.058. To get a better sense of the estimated elasticity, we use the point estimate to study a counterfactual scenario in which firms' financial constraints are removed. This scenario is equivalent to setting the index of financial constraints FC for all firms to the average value of the index calculated for firms categorized in the unconstrained group. In particular, we find that the index is on average 0.15 points higher for the constrained class with respect to the unconstrained class. Further, 59 percent of firms are categorized as constrained. We use these values to calculate the response of labor productivity to removal of financial constraints, given firm characteristics, in the Lithuanian firms:

$$0.59 * 0.15*0.058 \sim 0.51\%$$

Therefore, we find that under a scenario in which firms are not financially constrained, average firm level investment is expected to increase significantly by roughly 7.2 percent.

Besides these counterfactual scenarios, as shown in Table 9 and Table 10 in the appendix, past productivity is positively related to current productivity and investment, higher debt, and higher cash flow both increase investment and productivity. Investment is increasing in firm size and firm age, though the estimates for are not significant at 10 percent significance level, while size has a high explanatory power.

4.4 Financial Constraints, Firm Age, and Size

Firm size and firm age are negatively related to the measure of financial constraints in line with the finding of literature that smaller and younger firms have more difficulty getting access to liquidity to finance their investments. To explore this further, specification (2) of Table 4 includes the interaction of age with size and Table 6 summarizes these values. The number reported in each cell is the sum of the coefficients when the respected dummies are equal to 1. For example, the value reported in size large and age group 0-5 years, is the sum of dummies for large=1, age group 0-5 =1, and the interaction of the two terms. Note that no value is reported for small and age group 0-5 as these are the reference groups. Next, Table 6 suggests that for each size class, age and financial constraints are negatively related, i.e., younger firms of a given size group are more likely to be financially constrained.

As in Hadlock and Pierce (2010) our paper highlights the importance of firms' age and size in predicting the probability of being constrained. Additionally, the coverage of our dataset of SME and young firms allows us to uncover further trends that to the best of our knowledge have not been identified by the literature. We find that size, age, and financial constraints display a non-linear relationship. In particular, for young firms age group 0- 5), large firms are more likely to be financially constrained. This result is directly related to our classification scheme which captured both the desire and ability of firms to invest. Among young firms, while those that are large may be able to borrow more, it is likely that they are not getting the amount they desire to reach their optimal size while smaller firms may not be able to borrow as much but it is possible that their desire to borrow is not as strong. As firms grow older in particular for ages above 10 smaller firms are more likely to be financially constrained. Finally, the interaction of debt ratio with size suggests that higher debt leads to a higher probability of being constrained for smaller firms, while old firms having higher debt ratio have a higher probability of being constrained. The interaction of cash with age and size does not have a high explanatory power.

Table 6: Effect of Age and Size on the Likelihood of Being Constrained				
	0-5	6-10	11-15	15+
Small (10-49)	-	0.031*	-0.005	-0.057*
Med (50-249)	0.108***	0.102	0.028***	-0.082**
Large (250+)	0.091	0.070	-0.038*	-0.223***

* $p < .10$, ** $p < .05$, *** $p < .01$. This table shows the coefficients on firm age and firm si:1e as presented is specification (2) of Table 4. The reference group is small and young firms. Size is based on number of employees, and definitions are presented in parenthesis.

5. Conclusion

In this paper we provide evidence on the relationship between financial constraints, firms' investment choices and their labor productivity. Our analysis uses a unique dataset covering the entire population of Lithuanian firms during the period 2000–2018.

We used a classification scheme that categorizes firms into groups of constrained and unconstrained. The categorization is based on information from the asset side and the liability side of the balance sheet thus captures both the desire and the ability of firms to invest and/or borrow. We then used this classification scheme to construct a continuous measure of financial constraints by estimating an ordered probit model which relates the classification scheme to firm specific characteristics. As a final step, we used this measure to assess the implications of limited access to financing on investment and labor productivity.

Our results indicate that financial constraints significantly lower labor productivity and firms' investment decisions. In particular, our estimates show that removing these constraints is associated with an improvement in average labor productivity by .51 percent and investment by 7.2 percent. The results of our analysis indicate that providing better access to financing can indeed lead to significant gains in productivity and overall economic growth, if targeted at the appropriate population of firms. In the case of Lithuania, young and large firms are expected to show the greatest return to alleviating access to finance. A range of approaches can emerge that depends on the nature of the constraints that these specific firms are facing. In general, financial constraints could stem from the due diligence processes of creditors, lack of financial instruments available for the types of financing needs for these firms, awareness and knowledge of firms in financing options available to them, or reporting practices of firms, among others. Prioritizing efforts to identify these firms and to better understand the sources of constraints will help policymakers most effectively enhance the allocation of capital. Ultimately, this would lead to a more sustained economic convergence over the medium- and long-run.

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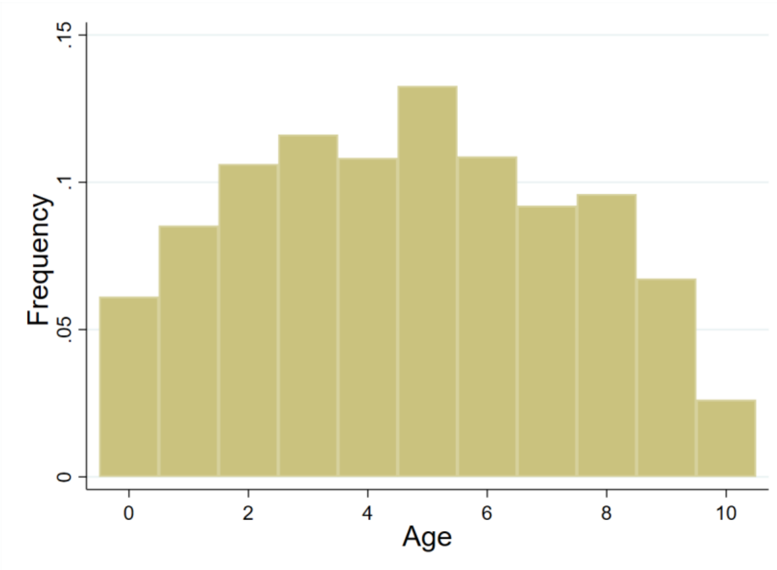
Appendix

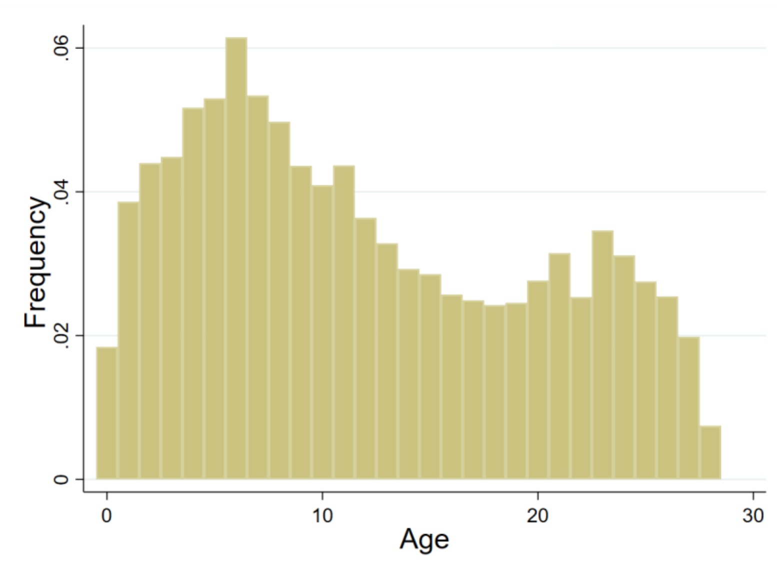
Firm's Age Distribution:

Figure 2: Share of Firms in Any Age Cohort in 2000



Note: Frequency refers to share among total firms in the sample.

Figure 3: Share of Firms in Any Age Cohort in 2018



Note: Frequency refers to share among total firms in the sample.

Firms' Age-Size Distribution:

Figure 4: Age Distribution by Firm Size in 2000

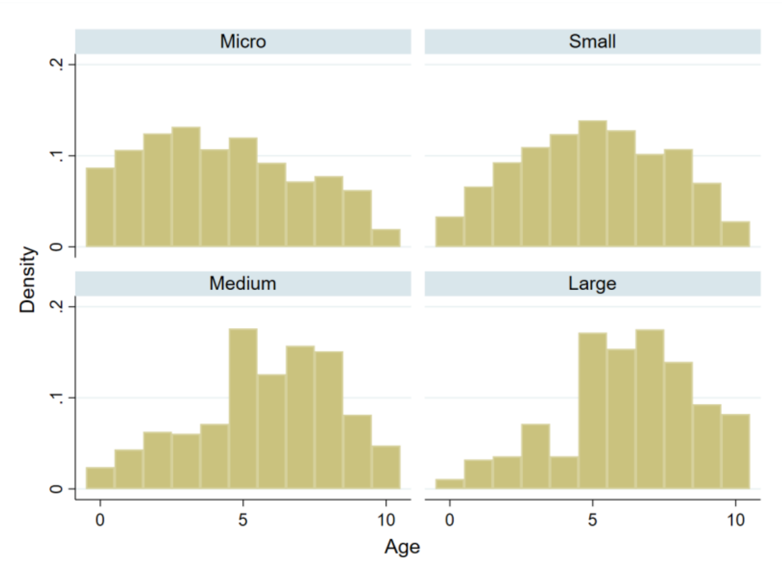
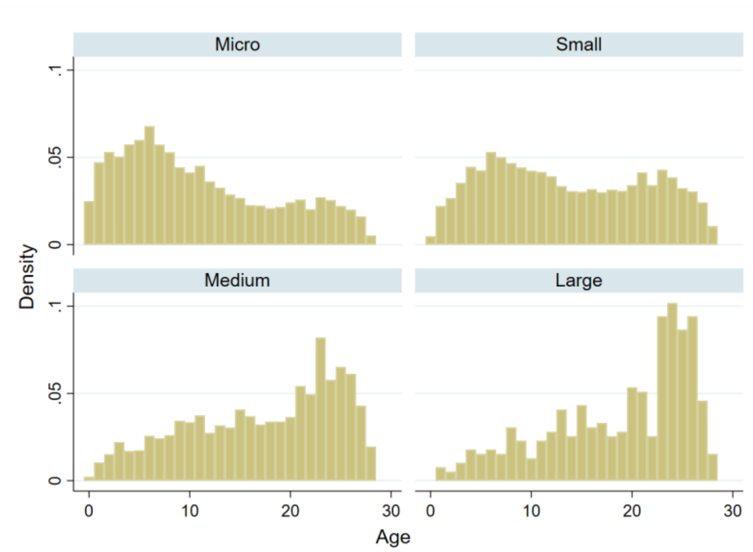
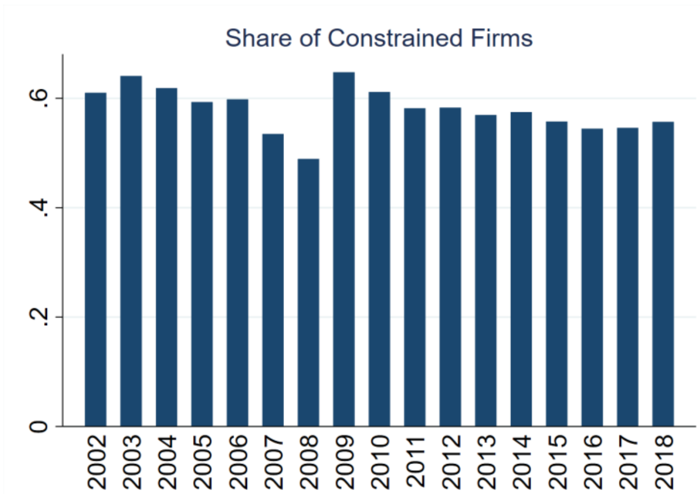


Figure 5: Age Distribution by Firm Size in 2018



Description of the Measure of Financing Constraint

Figure 6: Share of Constrained Firms



Note: Share is created according to the classification scheme in Table 2.

Table 7: Transition Matrix

Category	Unconstrained	Constrained	Total
Unconstrained	52.90	47.10	100
Constrained	28.65	71.35	100
Total	37.10	62.90	100

Notes: Constrained and unconstrained defined according to the classification scheme of Table 2. The Table shows probability of staying of switching to another class in the subsequent period.

Table 8: Probability of Being Constrained Based on Interest Rate

	$i \leq$ *median*	$i >$ *median*
2016	0.49	0.54
2017	0.48	0.54
2018	0.49	0.55

Table 9: Financial Constraints and Labor Productivity

	1) ln (productivity)	2) ln (productivity)	3) ln (productivity)	4) ln (productivity)
L.ln ((productivity)	0.255***	0.255***	0.254***	0.219***
	(0.00488)	(0.0121)	(0.0248)	(0.0242)
L.debt ratio	0.175***	0.177***	0.176***	0.157***
	(0.00855)	(0.0124)	(0.0261)	(0.0290)
L.cash to sales	-0.0230	-0.0226	0.00207	0.0343
	(0.0194)	(0.0237)	(0.0225)	(0.0278)
L.constrained	-0.0585***	-0.0616**	-0.135**	-0.120*
	(0.0203)	(0.0260)	(0.0612)	(0.0601)
L.ledium		-0.00185	0.0356**	0.0232
		(0.00933)	(0.0138)	(0.0229)
L.Large		-0.00228	0.0223	0.0489
		(0.0192)	(0.0340)	(0.0720)
L.age group 2		0.0198***	-0.00149	-0.0260
		(0.00637)	(0.0371)	(0.0426)
L.age group 3		0.0302***	-0.00558	-0.0356
		(0.0101)	(0.0510)	(0.0533)
L.age group 4		0.0340***	-0.0634	-0.125
		(0.0128)	(0.0631)	(0.0742)
L.med×L.constrained		-0.0671***	-0.0789***	
			(0.0178)	(0.0260)
L.large×L.constrained			-0.0478	-0.125
			(0.0642)	(0.110)
L.age group 2×L.constrained			0.0369	0.0605
			(0.0548)	(0.0576)
L.age group 3×L.constrained			0.0615	0.0874
			(0.0695)	(0.0628)
L.age group 4×L.constrained			0.182*	0.252**
			(0.0973)	(0.103)
Constant	3.350***	3.328***	3.375***	3.612***
	0.0238)	0.0523)	(0.130)	(0.120)
Time-Sector FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R-squared	0.755	0.755	0.755	0.762
Obs	95977	95977	95977	110770

Notes:
Standard errors in parentheses
$*$ p < .10, $**$ p < .05, $***$ p < .01
Age group 2: 6-10 years; Age group 3: 10-15 years; Age group 4: 15+
Specification (1); (2) and (3) exclude education; health and agriculture sectors.

Table 10: Financial Constraints and Investment

	1) ln (productivity)	2) ln (productivity)	3) ln (productivity)	4) ln (productivity)
L.ln ((productivity)	0.255***	0.255***	0.254***	0.219***
	(0.00488)	(0.0121)	(0.0248)	(0.0242)
L.debt ratio	0.175***	0.177***	0.176***	0.157***
	(0.00855)	(0.0124)	(0.0261)	(0.0290)
L.cash to sales	-0.0230	-0.0226	0.00207	0.0343
	(0.0194)	(0.0237)	(0.0225)	(0.0278)
L.constrained	-0.0585***	-0.0616**	-0.135**	-0.120*
	(0.0203)	(0.0260)	(0.0612)	(0.0601)
L.Iedium		-0.00185	0.0356**	0.0232
		(0.00933)	(0.0138)	(0.0229)
L.Large		-0.00228	0.0223	0.0489
		(0.0192)	(0.0340)	(0.0720)
L.age group 2		0.0198***	-0.00149	-0.0260
		(0.00637)	(0.0371)	(0.0426)
L.age group 3		0.0302***	-0.00558	-0.0356
		(0.0101)	(0.0510)	(0.0533)
L.age group 4		0.0340***	-0.0634	-0.125
		(0.0128)	(0.0631)	(0.0742)
L.med×L.constrained		-0.0671***	-0.0789***	
			(0.0178)	(0.0260)
L.large×L.constrained			-0.0478	-0.125
			(0.0642)	(0.110)
L.age group 2×L.constrained			0.0369	0.0605
			(0.0548)	(0.0576)
L.age group 3×L.constrained			0.0615	0.0874
			(0.0695)	(0.0628)
L.age group 4×L.constrained			0.182*	0.252**
			(0.0973)	(0.103)
Constant	3.350***	3.328***	3.375***	3.612***
	0.0238)	0.0523)	(0.130)	(0.120)
Time-Sector FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R-squared	0.755	0.755	0.755	0.762
Obs	95,977	95,977	95,977	110,770

Notes:

Standard errors in parentheses

∗ p < .10, ∗∗ p < .05, ∗∗∗ p < .01

Age group 2: 6-10 years; Age group 3: 10-15 years; Age group 4: 15+

Specification (1); (2) and (3) exclude education; health and agriculture sectors.

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