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Financial Investment Constraints. A Panel Threshold Application to German Firm Level Data.

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Financial Investment Constraints in Germany. A Panel Threshold Application to Firm Level Data.

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Abstract

This article tests the hypothesis that financial supply-side shifts help to explain the low-investment climate of private firms in Germany. The core contention is that a firm's financial position contributes to its access to external finance on credit markets. Special emphasis is put on small and medium-sized firms as these are assumed to face more restrictive access to external sources of funds. The application of a non-linear panel threshold model allows us to group firms endogenously according to their financial position. As potential threshold variables nine different balance sheet indicators are used. The results reveal a positive relationship between cash flows and fixed capital accumulation. Additional nonlinearity suggests that financially fragile firms rely more heavily on retained earnings. In contrast to frequent assumptions, firm size does not seem to be a relevant grouping variable in general with the only exception being micro firms for which the probability to fall into a financially constrained regime is higher compared to other companies.

JEL Classifications: A10, C23, D24, E22, E30, G31

Key Words: Firm investment, Balance sheet, Financial frictions, Credit rationing, SME, Non-linear panel

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1 Introduction

Private investment growth has received much attention in recent years as a consequence of the observed low growth in advanced economies since the outbreak of the recent great financial crisis (GFC henceforth) in 2008 (IMF, 2015, Ch. 4).[1] Different contributing factors of the sharp recent downturn in investments are discussed, ranging from increased economic and political uncertainty delaying investment decisions, over a slowdown in aggregate demand resulting in a decline in expected profits, to an increase in financial constraints caused by a crash on credit markets (IMF, 2015, Ch. 4). However, the persistently low fixed private investment rates realized in Germany are not intuitive on a first glance as average bank lending rates are low, German firms have increased their capital base *on average* during the past years, measures of credit constraints have come down considerably since 2010, and energy prices are on historical lows. We argue that the weak private investment dynamics observed on the aggregate level can be traced back to financial frictions on the microeconomic level, in particular leveraged enterprises face. This is in line with recent arguments made by the ECB that the weak recovery is mainly caused by financial constraints stemming from the supply side on credit markets (ECB, 2013).

First evidence of an empirical relationship between private fixed investments and credit provided to non-financial firms operating in Germany, is displayed in Figure 1. Between 2000 and 2012 the annual average growth rates of real gross fixed capital formation and real gross investment into machinery are 0.28% and 1.06%, respectively. After a temporary increase in 2005, private investments sharply collapsed as a result of the GFC. Between 2008 and 2009 real gross fixed capital formation dropped by almost 15% and real gross investment into machinery even by 25%. Throughout the whole period, low private investment rates were coupled with slow credit growth to non-financial firms (around 2.3% on average). During the GFC, overall credit growth remained still positive (except in 2010 when the growth rate was about -2.5%) but at a decreasing rate. It should also be mentioned that according to Lenger and Ernstberger (2011) some firms in Germany already faced credit constraints between 2000 and 2006 which helps to explain the low investment climate since the early 2000s.

Additional evidence comes from recent ECB bank lending surveys, which indicate that hampered access of non-financial firms to external finance has intensified the weak recovery since 2008. Supply-side driven financial frictions have tightened as banks' perceptions of risk in-

[1] Monetary policy decision makers are interested in investment dynamics as the efficacy of transmission mechanisms of monetary operations and its propagation effects on the business cycle crucially depend on the understandings of the determinants of firm-level investments. Furthermore, the issue of capital accumulation is also closely related to growth and innovation aspects, market competition; and hence a key variable for industrial policy decisions.

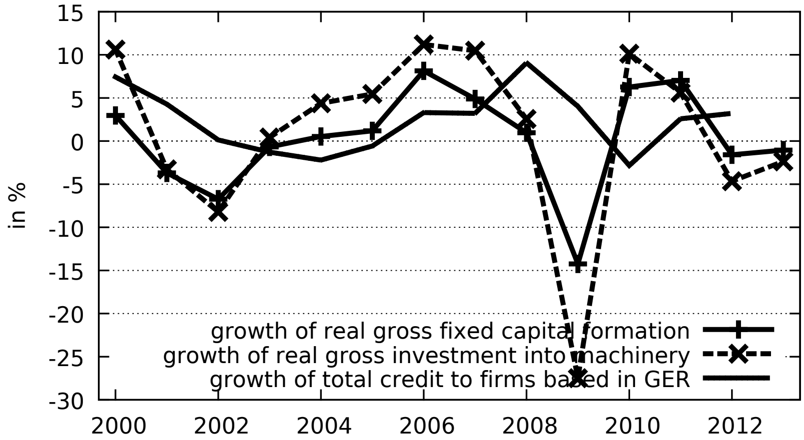


Figure 1: Growth of real private gross investment in GER, and domestic bank loans to non-financial firms in Germany. Source: Destatis and Bundesbank, own calculations. Sample: 2000–2013.

creased and reached its highest level at the peak of the crisis. Lending rates as well as lending standards were tightened between 2006 and 2009. In total, this development has been a source of reduced investments (ECB, 2013). However, empirically one observes that firm-level investment dynamics show substantial cross-sectional differences over the business cycle. For instance, credit availability is more severely restricted during recession periods for small and medium-sized enterprises[2] (SMEs henceforth) compared to large firms (Duchin et al., 2010; ECB, 2014; IMF, 2015). Given that 98% of all German firms belong to the category of SMEs, employing about 55% of all employees and generating 55% of total value added in Germany[3] (Vetter and Köhler, 2014, p. 2), a firm-level specific analysis is crucial.

There is now a large theoretical literature that investigates the role of financial factors in company investment decisions. This strand of literature criticizes the Modigliani and Miller (1958) perspective which is also prevalent in standard RBC and New Keynesian models with rigid wages and prices that a firm's balance sheet position and cash flow is irrelevant for their investment decisions. Under perfect capital markets, every investment project will be financed if the expected present discounted value of the profits is greater than the cost, as under these conditions a lender can fully protect himself against credit default However, imperfections on capital markets expose the lender to credit default risk. Based on the insight that a loan contract comprises the lender's agreement to transfer funds immediately to the borrower who only promises to repay in the uncertain future, actual and contractual repayments may diverge for principally two reasons: First, the borrower is unable to raise the required surplus due to failure

[2]Here SMEs are defined as firms with less than 250 employees and an annual turn of less than 44 Mio. Euro.
[3]It should be noted that the statistics are very similar across the EMU countries.

of the investment project, second the debtor is unwilling to repay accordingly to the contract. Both possibilities expose the lender to the risk that the debtor defaults. Thus, financial market imperfections help to explain specific features of financial markets like the characteristics of debt contracts such as the role of collateral, credit limits and credit and/or equity rationing phenomena as an equilibrium outcome. On the aggregate level, macroeconomic models incorporating financial frictions are used to explain the source of financial market perturbations as well as the amplification and persistence of shocks (Bernanke and Gertler, 1989; Stiglitz and Greenwald, 2003).[4]

Financial market imperfections can be explained in terms of imperfect, costly and asymmetric information between creditors and debtors (see Jaffee and Russell (1976); Stiglitz and Weiss (1981)), transaction costs[5], bankruptcy costs, costs associated with verifying the states of nature (see e.g. Townsend (1979); Williamson (1986, 1987)) and costs of writing and enforcing contracts (Stiglitz, 2015, p. 14) as well as the importance of risk-averse lenders (Fischer, 1986; Größl-Gschwendtner, 1993).[6] A key consequence of imperfect capital markets is that financial variables such as retained earnings or other balance sheet items play an important role for firm investment decisions and the availability of external funds.

Additionally, the distinction between firm sizes takes up a crucial point in the literature on financial frictions. SMEs are more likely to face capital market imperfections due to a variety of arguments: Firm size matters for the degree of economies of scale effects, and hence for productivity and cost differences. Furthermore, SMEs have less opportunities to diversify their product portfolio, geographical business areas and access to external finance. Also SMEs are assumed to be informationally more opaque, it is difficult for them to provide high quality collateral, and they face higher default risks. This makes them more sensitive to external market shocks. Overall, SMEs operate in a totally different economic environment compared to large companies (Berger and Udell, 1998, 2006). Typically, SMEs are more dependent on bank lending

[4]Early exceptions stressing financial considerations for firm investment demand are Kalecki (1937); Duessenberry (1958), Robinson (1966) and Minsky (1975). These authors argue that investment demand is constrained by the availability of financing a firm can internally generate or obtain from external sources. However, these approaches have not been explicitly derived from first-principles, which is deemed to be standard nowadays. Nevertheless, their theoretical implications share key aspects with the modern approaches to credit and investment.

[5]Asymmetrically distributed information is existent, for instance, if the borrower has more information on a project's risk in comparison to the lender. This poses principal-agent conflicts if the objective functions of both agents deviate which leads to conflicting interests. As already mentioned before, limited liability of the borrower leads to default risk, implying that the creditor bears the default costs. To make lending feasible in this case, the creditor will demand a collateral which covers the potential loss. The third element refers to credit rationing which may occur as an equilibrium outcome.

[6]This latter less known approach models banks as being risk-averse against default operating under imperfect-capital markets and facing the possibility of unforeseen events are expected to behave. Under such scenarios phenomena like credit rationing are likely to emerge even under the assumption of symmetric information between creditors and debtors.

and it is harder for them to acquire alternative sources of financing such as debt issuance which is associated with high fixed costs. Also there is evidence that credit availability is more severely restricted during recession periods for SMEs compared to large firms (Duchin et al., 2010; ECB, 2014).

These theoretical implications and the empirical evidence demand an analysis of investment dynamics on the micro-level, as conducted in this study. We construct a representative company panel data set for firms located in Germany, covering the period 2006 to 2012. This data set is used to estimate the empirical investment equation and to investigate the role played by financial factors. Specifically we want to compare the investment model for firms characterized by differences in their financial status (financial constrained vs. unconstrained firms). We estimate a nonlinear investment equation incorporating threshold effects, and test various hypotheses.[7] The reduced form investment equation controls for various firm-level and macroeconomic level effects as well as for the effect of cash flow on investment. As outlined before, an effect of current cash flow on investment can be seen as an indirect hint for financing constraints. We also focus in the question whether the intensity of credit constraint differs between financially solid and less solid or fragile firms.

The well-known line of research initiated by Fazzari and Athey (1987) and Fazzari et al. (1988), has applied different indicators to split the sample into financially solid and fragile firms before the investment equation augmented by financial variables is estimated. For instance, Fazzari et al. (1988); Bond and Meghir (1994) have used the dividend-payout ratio as firm's signal of financial soundness, Hoshi et al. (1991); Engel and Middendorf (2009); Lenger and Ernstberger (2011) applied the degree of bank affiliation as a sample-splitting variables referring to the literature on relationship-lending (Petersen and Rajan, 1994; Boot, 2000), Whited (1992) argues that bond rated firms are typically less opaque than non-rated ones, and others have used firm size and firm age as signaling indicators (Oliner and Rudebusch, 1992; Gertler and Gilchrist, 1994; Hubbard, 1998; Harhoff, 1998; Audretsch and Elston, 2002). An indirect approach was suggested by Fuss and Vermeulen (2006) who identified periods when firms suffer from exceptional liquidity

[7] Typical alternative models applied in the literature are the error-correction model or the Euler-equation specification. Even though these specifications use the GMM methods which controls for possible biases due to unobserved firm-specific effects and endogeneity issues and captures the influence of expectations properly, these models do usually not allow for nonlinearities (see Bond et al. (2003)). However, there are objections to the Euler equation approach. First, the test on over-identifying restrictions may not reject the null hypothesis of no financial constraints if the available sample is too short in the time dimension. This is especially the case if the tightness of the constraint only marginally changes over time (Schiantarelli, 1995, p. 190). Second, instability, for instance of adjustment costs over time, may lead to a rejection of the null of perfect capital markets even though firms do actually operate under such circumstances. Thus, misspecification of production technology, adjustment costs or inappropriate instruments may bias the empirical outcomes. Also the estimation of the Euler equation does not allow to quantify the degree of market imperfections (Fazzari and Petersen, 1993, p. 329).

shortages and hence financing constraints become binding, while Chirinko and von Kalckreuth (2002) use a discriminant analysis to compile a measure of creditworthiness by means of an index comprising balance sheet information.

However, these sample-splitting procedures suffer from methodological drawbacks. First, some of the grouping-variables, for instance the dividend-to-payout ratio, are likely to be endogenous, and it may be plausible that firms adjust their dividend-payout ratio to their investment plans rather than the other way around (Hansen, 1999). Also, firms are typically classified according to a single indicator alone which is a strong assumption as other indicators may be relevant as well. However, the inclusion of further control variables may increase the dimension of the econometric model substantially, affecting statistical inference negatively. Third, the belonging of a firm to a specific group is often assumed to be fixed over the sample period. It is more realistic to assume that a firm switches from one group to another during its life-time (Hu and Schiantarelli, 1998). For further issues on sample separation criteria see Schiantarelli (1995, p. 192 ff.). Facing these critical points, Hu and Schiantarelli (1998) and Hansen (1999) have suggested alternative separation frameworks. Both authors apply methods which separate groups endogenously using a data-driven approach.[8] Alternatively, Hansen derives the statistical properties of a piecewise-linear panel model with fixed-effects. He proposes an algorithm to test for multiple thresholds and derives the asymptotics for further inference. This threshold panel model is in fact a special case of the more general switching model but much simpler to implement and to estimate. In the following we introduce Hansen's idea in more detail .

The main contribution our this article to the literature is twofold: First, our empirical work exploits a database which comprises listed as well as unlisted companies from various industrial sectors of different firm sizes and legal statuses in Germany using recent data. Only few previous studies have exploited such heterogeneous datasets. Second, we employ an empirical data-driven sample-split procedure to differentiate between financially constrained and unconstrained firms. This helps us to circumvent the often applied but to some degree *ad hoc* methods, as named before. The procedure relies on the panel threshold regression method suggested by Hansen (1999). As the regime is latent, one needs a signal to extract the unobservable from observables. As observables we use different balance sheet items such as leverage, interest coverage ratio, measures of solvency and collateral as well as common factors comprising different balance sheet variables.

[8]More concrete, Hu and Schiantarelli estimate endogenous switching regressions. They use different balance-sheet indicators which trigger the probability of a firm being in a constrained or unconstrained regime, respectively. The cash-flow-to-investment sensitivity depends on the regime a firm operates in.

In line with recent studies using panel data on the firm-level (Bond et al., 2003; Martinez-Carrascal and Ferrando, 2008; Engel and Middendorf, 2009; Lenger and Ernstberger, 2011) the main result of our article reveals that the weak private fixed investment performance of firms in Germany between 2006 and 2012 can be explained by financial constraints. We find that rather than firm size, as frequently argued, a firm's financial position crucially matters for the intensity of such constraints. For various specifications, there is statistically robust evidence that financial variables such as lagged cash flow rates are positively correlated with realized fixed private investment rates. Furthermore, the cash-flow-to-investment sensitivity is non-linearly related to a firm's financial position. We show that neglecting existing threshold effects results in biased coefficient estimates, and underrates the importance of financial constrains firms face. The capital accumulation rate of firms with short-term debt over total cash at hand ($1/liquidity$) larger than 13.6, debt-to-cash-flow ratios ($1/solvency$) above 4.2, leverage ratios (lev) above 1.1 or dynamic debt shares ($dyndebtshare$) above 0.041 depends substantially stronger on internal funds in comparison to financially solid enterprises. This indicates that financially robust firms are less credit constrained than fragile firms. Interestingly, firm size is not found being a reasonable predictor for a firm's degree of financial constraints. Using a measure of solvency or debt share, according to our data about 30% to 40% of all firms in the sample belong to a financially solid regime facing low levels of financial restrictions. This holds for all firm types with the only exception being micro firms (less than 20 employees), for which the share of firms operating in a solid regime is found being lower. Hence, micro firms were hit hardest during the GFC, such that many of these enterprises switched from a solid to a rather fragile financial regime.

This paper proceeds in five sections. In Section 2, we review the literature on credit markets imperfections and financial constraints on firm investment. Section 3 introduces the methodological approach and we selectively review the empirical literature on firm-level fixed-investments. The econometric approach and the fixed-investment estimation results are presented and discussed in Section 4. Section 5 concludes, while details of the dataset and its construction can be found in the Appendix.

2 The Empirical Investment Equations

Two different econometric models of firm-level investment are estimated. The models specified are a static linear fixed-effects model and a static nonlinear threshold model which are described in the following.

2.1 The linear fixed-effects model

Fazzari and Athey (1987) and Fazzari et al. (1988) proposed an alternative way testing for financial frictions by analyzing the relationship between investment, cost of capital and internal funds. According to the standard literature, Tobin's q (1956) should fully predict firm investment decisions on perfect capital markets. Hence, financial factors such as cash flow should have no additional predictive power for investment dynamics. In order to test this hypothesis, a standard investment function augmented by financial factors is estimated. If investment depends on other financial variables, conditional on Tobin's q, this is interpreted as indirect evidence for existing financial constraints. However, as we have listed as well as unlisted firms in our dataset, there is no possibility to construct a measure of Tobin's q which should capture expected profitability for the latter categories of firms. This issues is well known, and we follow previous studies using the same or similar datasets to ours (see e.g. Lenger and Ernstberger (2011)).

The following augmented linear investment function will be estimated

$$\frac{I_{it}}{K_{it-1}} = \mu_i + \beta \left(\frac{CF_{it-1}}{K_{it-2}} \right) + \alpha_1 D_{it-1} + \alpha_2 D_{it-1}^2 + \phi X_{it} + e_{it} \qquad (1)$$

where the disturbances are assumed to be stochastic with e_{it} independent and identically distributed with zero mean and constant variance σ_e^2; the set of regressors is assumed to be independent of the e_{it} for all firms i and periods t. The dependent $\frac{I_{it}}{K_{it-1}}$ is a scalar, the scalar μ_i denotes a unit-specific intercept, and I, K and CF refer to gross nominal firm investment, firms' nominal capital stock, and the financial variable measure namely nominal cash flow. Lagged values are used to avoid possible endogeneity issues. The additional term of lagged cash flow rates allows us to investigate the role of financial variables. It is expected that the investment-to-cash-flow sensitivity increases (maybe in a non-linear manner) in the degree of capital market imperfections. Hence, for unconstrained firms, one expects *a priori* a low cash flow sensitivity of investment or no effect at all, as any positive net-present value project could fully be financed by external funds. Variable D_{it-1} corresponds to an additional balance-sheet variable (to be described in Section 3) different from cash flow. Also the squared value of D_{it-1} is added to capture additional nonlinear effects.[9] Furthermore, X_{it} is a p by 1 vector including p additional control variables both on the firm- as well as macroeconomic level while ϕ is a 1 by p vector associated with the corresponding coefficients. The set of control variables on the micro-level comprises the lagged number of workers (in logs) (w_{it-1}), lagged growth of real sales revenues

[9]The balance sheet variable D is added here as it will serve as the threshold variable in the nonlinear model which will be described below. This allows us to compare the linear with the nonlinear model.

(gt_{it-1}), lagged real return on investment (roi_{it-1}) and its squared value (roi^2_{it-1}), the current depreciation rate (d_{it}) and its squared value (d^2_{it}). Furthermore, we add three macroeconomic control variables namely the current real output gap (gdp_t), a dummy which captures a permanent level shift in the conditional mean after the GFC in 2007 ((gfc_t, takes zero up to 2007 and unit afterwards) and an interaction term between this dummy and firm size approximated by the number of workers ($gfc_t \cdot w_{it}$):

$$X'_{it} = [w_{it-1}, gt_{it-1}, roi_{it-1}, roi^2_{it-1}, d_{it}, d^2_{it}, gdp_t, gfc_t, gfc_t \cdot w_{it}] \,.$$

Growth of real sales revenues captures the real side of investment decisions. For instance, the variable encompasses potential accelerator effects which may capture further investment demand factors. Additionally, real return on investment and its squared value are added to the specification.[10] Both growth of real sales revenues and the real rate of return also capture profit expectations on imperfectly competitive output markets (Himmelberg and Petersen, 1994; Lenger and Ernstberger, 2011). Expected profitability may also help to approximate prospective profit opportunities of an investment project (Fazzari et al., 1988). The consideration of these information is an attempt to argue against the claim that a positive cash flow effect on investment is a pure result from omitted demand factors (Fazzari and Petersen, 1993, p. 333).[11] The number of workers per firm controls for differences in the accumulation rate due to firm size. The effect of firm size is ambiguous: it is typically positively related to firm age, and older firms are assumed to be more diversified and transparent as they may have longer track records with investors, creditors, suppliers and customers. Overall, this may make older companies less prone against bankruptcy risks, and hence associated agency costs should be rather low. On the other hand, small firms may face lower agency costs as their ownership structure (typically a small number of managers own large portions of the firm) is less prone to conflicting interests. Thus, in total the effect of firm size is ambiguous. Current depreciation and its square value are added as another important source of internal funding as it accounts for a substantial fraction of total funding

[10] We did not consider the squared value of gt_{t-1} as it was in none of the specifications statistically significant.

[11] A short note is provided on a related problem. The standard q-model of investment with perfect capital markets predicts that investments react to a positive output shift not due to higher levels of retained earnings today but as expected profitability increases as it makes capital more valuable. High cash flows may reflect a firm's sound market position and indicate high future profitability. Hence, current cash flow will be correlated with future profitability. This makes it hard to distinguish whether investment changes because of changes in current cash flow or due to expected profitability shifts. As a result, one will observe a positive correlation between current cash flow and investment even in the absence of financial constraints as cash flow simply proxies future expected profitability (see Schiantarelli (1995, p. 180ff.) for more on this). Indeed, Cummins et al. (2006) find in their firm-level study that the cash-flow-investment relationship breaks down after controlling for expected earnings. This finding is robust even among apparently financially constrained firms, and may explain why firm fundamentals are more relevant than the presence of financial constraints in the U.S. economy – at least according to these authors. The growth of real sales revenues should, however, appropriately capture these expectation effects and ensure that cash flow actually does not capture future profits and investment opportunities but current profitability.

next to retained earnings (Bundesbank, 2012). The econometric specification also comprises additional macroeconomic variables to control for non-idiosyncratic effects. The contemporaneous real output gap accounts for business cycle effects and reflects the current state or climate of the overall economy which might also affect optimal investment. The dummy variable gfc_t corrects for level shifts in accumulation rates due to the recent financial crisis. Additionally, the interaction term between gfc_t and $w_{i,t}$ controls for different impacts of the crisis according to firm size. It might be the case that larger firms were better able to cope with the crisis, e.g. due to better market or product diversification and more business experience. More detailed information on the variable construction can be found in the Data Appendix.

We closely follow Fazzari et al.'s framework in this paper, but augment the empirical analysis by allowing for a data-driven way to group firms into constrained and unconstrained ones endogenously. The approach will be described after a brief overview of the existing empirical literature.

2.2 The threshold fixed-effects model

Whereas the linear model assumes constant coefficients, the nonlinear model allows for regime-dependent effects. Namely, we want to model the effect of cash flow on investment, α_1 in eq. (1), being a function of the value of the balance sheet variable $D_{i,t}$. The panel model proposed by Hansen (1999) belongs to the class of static nonlinear panel models. The basic idea is to split the sample into a small number of classes (regimes), before the regime-dependent and -independent coefficients are estimated in a second step. The transition across regimes is assumed to be instantaneous (non-gradually) and driven by a transition variable D being below or above a—to be determined—threshold value γ.[12] The structural equation for a 2-regime (single threshold) model, taken for illustration, is given by

$$\begin{aligned} \frac{I_{it}}{K_{it-1}} &= \mu_i + \beta_{LOW}\left(\frac{CF_{it-1}}{K_{it-2}}\right)\mathbf{I}(D_{it-1} \leq \gamma) + \beta_{HIGH}\left(\frac{CF_{it-1}}{K_{it-2}}\right)\mathbf{I}(D_{it} > \gamma) \\ &+ \alpha_1 D_{it-1} + \alpha_2 D_{it-1}^2 + \phi X_{it} + e_{it} \end{aligned} \tag{2}$$

[12] A more general class of models is known as smooth transition regression models (see Gonzalez et al. (2005); Fok et al. (2005) on panel models). The parameters are allowed to change smoothly between multiple regimes, depending on the value of a transition variable and critical location values. However, theoretically it is quite plausible to assume that lenders classify in a manner reasonable in line with threshold behavior. For instance, banks have a standard classification scheme and rank potential clients according to a vector of bankruptcy indicators which is consistent with a threshold approach. Furthermore, smooth transition models are much more complex to estimate. The estimation of the non-linear model part involves complex optimization issues and standard procedures such as grid searches may result in a local instead of a global optimum. Nevertheless, this does not rule out the application of this approach in future work.

where all definitions remain as in model eq. (1) except that the vector $\left(\frac{CF_{it-1}}{K_{it-2}}\right)$ (here only a scalar, namely the cash flow rate) is regime-dependent, $I(\cdot)$ denotes an indicator function and γ is the threshold value corresponding to the threshold variable D_{it-1}. The indicator term takes unity if the threshold variable exceeds the threshold value γ and otherwise zero. Thus, the pre-period observable threshold value signals in which regime the firm operates in. The composition of the model involves the regime-independent coefficients μ_i, α_1,α_2 and ϕ as well as the regime-dependent effects of cash flow on the investment rate captured by the respective coefficients β_{LOW} and β_{HIGH}. The subscripts *LOW* and *HIGH* may refer to regimes where the balance sheet threshold variable D (for instance firm leverage) is below γ or above. The economic meaning of the regime (e.g. when $D_{it-1} \leq \gamma$) may be linked to a firm whose leverage is below a certain critical value which is associated with low (expected) default probability while a firm for which $D_{it-1} > \gamma$ may be characterized by a fragile balance sheet situation. Instead of classifying firms into specific regimes in a *ad hoc* manner, as often applied in past studies, firms are allowed to switch from one regime to other over time, even though the threshold value γ is time-invariant.[13] The assumption that e_{it} is $i.i.d$, requires that lagged dependent values are not included (Hansen, 1999, p. 347). The regression model is estimated for $i = 1, ..., n$ firms and $t = 1, ..., T$ observations. The analysis holds for fixed T as $n \to \infty$. It should be noted that the model can easily be extended along those lines to allow for more than a single threshold.

For a given γ, the regime-dependent β-coefficients can be estimated by OLS after the fixed effects transformation. In order to estimate γ, Chan (1993) and Hansen (1999) have shown the validity of the least square technique in this context:

$$\hat{\gamma} = arg\, min(\gamma)\, S_1(\gamma)\ . \tag{3}$$

The scalar $S_1(\gamma)$, the sum of squared errors (SSE) of the model specification with a single threshold, only depends on γ through the indicator function. The sum of SSE is a step function with at most nT steps occurring at distinct values of the observed threshold variable D. A standard procedure is to sort the distinct values of the threshold variable in an ascending order and to eliminate the smallest and largest η-% values. Next, one can search for $\hat{\gamma}$ over the N

[13] However, an inherent assumption of this framework is that the regime-dependent effect, which is supposed to capture cross-sectional heterogeneity across firms, is assumed to be constant over time. Recently, Bordo and Haubrich (2010) have emphasized that historically the credit channel is strongest during economic downturns. This is somehow confirmed by the empirical results obtained by Gaiotti (2013) based on firm-level Italian data. Gaiotti argues that the impact of bank credit on a firm's investment is time-varying and strongest during contraction periods when alternative sources of finance also become restricted. Nevertheless, this issue is left open for future research as the simultaneous consideration of time-varying effects would require a more complex modeling framework. Additionally, as the time dimension of the panel is rather small, it remains under debate how much time-variation actually can be found in the data.

remaining values of γ by running regressions over all N values. The estimate of $\hat{\gamma}$ is given for the regression with the smallest SSE. Hansen (1999) suggests to divide the N values of the set of γ values into specific quintiles which reduces the number of regressions performed but nevertheless is most likely to be sufficiently precise.

The null hypothesis of no threshold and its alternative of a single threshold are expressed as:

$$H_0 : \beta_{Low} = \beta_{High} \text{ vs. } H_1 : \beta_{Low} \neq \beta_{High} \,. \tag{4}$$

This hypothesis can be tested by a standard LR test. As the threshold parameter is not identified under the null hypothesis, the distribution of the test statistics is non-standard (Andrews and Ploberger, 1994; Hansen, 1996). However, the FE model belongs to the class of models considered by Hansen (1996), and his proposed bootstrap procedure can be applied to simulate the asymptotic distribution of the LR test based on the test statistics

$$F_1 = \frac{S_0 - S_1(\gamma)}{\hat{\sigma}^2} \tag{5}$$

where S_0 and S_1 refer to the sum of squared errors under the null and the alternative, respectively. For more information on the inference part and determination of multiple thresholds see Hansen (1999).[14]

The described approach has two major advantages: First, the threshold values are endogenously determined allowing for the classification of firms according to their financial position in a data-driven way. Second, the different regime models are sequentially tested against each other using a bootstrap technique. This allows one to determine empirically the number of regimes or groups of firms. In fact we test for multiple thresholds in the application below. In a first step a linear model is tested against a two-regime (single threshold) model. If the null of linearity against a two-regime model is rejected, the null of a two-regime against a three-regime model is tested, and so on.

[14] For the following empirical applications a grid with 300 quintiles after eliminating the $\eta = 5\%$ extreme values of the threshold variable is used. To compute the simulated asymptotic distribution of the LR test, we run a bootstrap procedure (draw with replacement from the empirical distribution) with 999 iterations. All computation is done using the open-source econometric software package `gretl` (Cottrell and Lucchetti, 2013). The code is available from the author upon request. The original `GAUSS` code is provided by Bruce Hansen on `http://www.ssc.wisc.edu/~bhansen/progs/joe_99.zip`.

3 Data

3.1 Data description

The largest German credit rating agency Creditreform and Bureau Van Dijk provide the DAFNE database used in this paper. The database comprises historical accounting data of a representative pool of German firms for the period between 2006 and 2012. Only firms from non-financial and non-public industry sectors having their main activities in mining, manufacturing over construction to information and communication are selected; see for details the Data Appendix. The final panel includes stock companies, limited liability companies and others. Limited liability companies represent the most prevalent legal firm type in Germany. The dataset is corrected for missing values, outliers and implausible values. Again we refer to the Data Appendix for details on data manipulation.

The econometric analysis is based on a balanced panel for three reasons. First, the econometric technique applied requires balanced panel data (Hansen, 1999). Second, a balanced panel eliminates the problem of biased estimates of the threshold parameter due to changing sample compositions over time. Last, as we want to asses the evolution of a firm's financial position and its impact on investment, we need to monitor firms over the whole time period. The number of valid observations depends on the variables considered as the number of missing values differs among the set of potential threshold variables. In total, the number of cross-sectional units ranges between 214 and 268, with the exception of the two factor variables ($factor1$ and $factor2$) for which only about 65 units exist respectively.

The dependent variable is the investment rate which is defined as the change in gross tangible fixed assets (equivalent to the capital stock) over pre-period gross tangible fixed assets , $\frac{I_{it}}{K_{it-1}}$. This definition of capital is widely used and assumes that capital is homogeneous (Barnett and Sakellaris, 1998, p. 268). Cash flow is measured by current retained earnings re-scaled by the lagged capital stock, $\frac{CF_{it}}{K_{it-1}}$, and often named the cash flow rate. The current depreciation rate is measured by current depreciation on fixed assets (DP_{it}) over pre-period tangible fixed assets, $d_{it} = \frac{DP_{it}}{K_{it-1}}$. Firm size is approximated by the number of workers (in logs), w_{it}, real sales revenue (gt_{it}) is nominal sales revenue deflated by the GDP price level and the real rate of return refers to nominal return on investment minus the GDP price level inflation rate. The real GDP output gap measure, gdp_t is obtained from the AMECO database and the dummy gfc_t takes zero for all observations up to 2007 and unit otherwise.

As it remains unclear which balance sheet item may contain predictive information on a firm's financial position, we specify a number of models using nince different balance sheet measures as potential threshold variables, D_{it}. The variables used reflect a common selection of balance sheet items to predict corporate defaults in practice, as shown by the reviewed literature as well as the recent survey by Silva and Carreira (2012).[15] Also, it is quite standard in the macroeconomic literature to measure bankruptcy risk by balance sheet variables. Early approaches can be found in Kalecki (1937) and Minsky (1975, 2008). For more recent applications see e.g. Gertler and Gilchrist (1994). Additionally, we conduct a principal component analysis comprising a vector of our seven balance sheet measures to capture common factors among those items. Common factors may contain superior predictive information for a firm's financial position and thus their investment decisions. The set of balance sheet items, D, consists of:

- lev_{it}, Total liability to total equity ratio as a measure of leverage
- $lglev_{it}$, Total long-term liability to total equity
- $intcf_{it}$, Net interest expenditures over cash flow as a measure of interest coverage ratio
- $1/collat_{it}$, Inverse of the sum of the stock of inventory, tangible assets and cash holdings to total tangible assets as a measure of collateral
- $1/solvency_{it}$, Inverse of cash flow to total liability
- $1/liquidity_{it}$, Inverse of cash at hand over short-term liability
- $dyndebtshare_{it}$, Dynamic debt measure
- $1/factor1_{it}$ Inverse of first factor of the principal component analysis including lev_{it}, $lglev_{it}$, $intcf_{it}$, $collat_{it}$, $solvency_{it}$, $liquidity_{it}$ and $dyndebtshare_{it}$.
- $1/factor2_{i,t}$ Inverse of second factor of the principal component analysis including lev_{it}, $lglev_{it}$, $intcf_{it}$, $collat_{it}$, $solvency_{it}$, $liquidity_{it}$ and $dyndebtshare_{it}$.

Calculating the inverse for some of the variables simply enhances interpretation, as a low value is now associated with a solid firm's balance sheet while high values (may) refer to a fragile one. The inverse of $factor1$ is positively correlated with lev ($\rho \approx 0.81$), $lglev$ ($\rho \approx 0.70$), $intcf$ ($\rho \approx 0.69$) and $dyndebtshare$ ($\rho \approx 0.75$), and negatively with solvency ($\rho \approx -0.81$) but not at all with collateral. The inverse of $factor2$ is strongly positively correlated with collateral and

[15] See for instance Moody's premier private firm probability of default model for the German market which relies heavily on financial ratios as predictor variables. URL: `http://www.moodysanalytics.com/~/media/Brochures/Enterprise-Risk-Solutions/RiskCalc/RiskCalc-Germany-Fact-Sheet.ashx`.

liquidity ($\rho \approx 0.67$). Thus, both factors capture specific but different balance sheet signals. For details on the principal component analysis, see Table 7 in the Appendix.

In order to present some basic features of this dataset, firms are grouped according to the number of workers (W) as follows:[16]

- Micro firms: $W < 20$
- Small firms: $20 \geq W < 50$
- Medium firms: $50 \geq W < 250$
- Large firms: $250 \geq W < 1000$
- Big firms: $W \geq 1000$

About 20% of all firms in the sample are stock corporations, almost 70% are classified as limited liability companies (LLC) while other legal types account for about 10%. A decomposition according to firm size reveals that 55% of all firms fall into the category of small and medium-sized firms (SMEs) while about 5% are micro firms. Large companies represent about 30% and big ones about 10% of all firms in our sample.

3.2 Descriptive statistics

Table 1 reports the median values of the variables used in our econometric analysis according to firm size between 2006 and 2012. The investment rate (I_t/K_{t-1}) is lowest for micro firms (0.03) and slightly increases in size. However, the real rate of return (roi_t) is about 0.03 for micro, large and big firms but about 0.05 (0.04) for small (medium) companies. The growth of real sales revenues (gt_t) is lower for SMEs compared to larger firms. The data indicate that big and large firms are slightly less leveraged compared to smaller companies. The median leverage (lev_t) of micro firms and SMEs is around 1.5 whereas the value for large firms is 1.4 and 1.2 for big companies. In terms of long-term leverage ($lglev_t$) no clear tendency is observable as the long-term leverage is 0.59 for small companies, 0.7 for medium and large ones and highest for micro firms (0.78). Overall there are some indications that micro firms and SMEs issue relatively more debt and a higher share of long-term debt instruments in comparison to larger firms. A

[16] Note that this definition slightly deviates from the official one used by the ECB for their *Survey on the access to finance of enterprises*: micro firms employ 1-9, small enterprises 10-49, medium-sized firms 50-249, and large enterprises more than 250 employees. URL: `https://www.ecb.europa.eu/stats/money/surveys/sme/html/index.en.html`

similar tendency can be observed for the dynamic debt share ($dyndebtshare_t$) where again we find the highest median values for micro firms (about 0.07) and slightly lower ones (0.05) for the remaining companies. However, even though micro firms are the most indebted firm category, their interest coverage ratios ($intcf_t$) are the lowest ones (0.03) while this measure is much higher for larger firms with about 0.14. It is interesting to see that small firms hold higher liquidity rates ($1/liquidity_t$) with a median value of only 1.82 in comparison to big firms (8.56). This could be explained by the fact that small firms use liquid means to be able to compensate external shocks quickly.[17] However, the large cross-sectional standard deviation of this measure makes it difficult to derive a string correlation with firm size here. Nevertheless, the solvency measure ($1/solvency_t$) indicates that micro firms are more financially fragile according to this measure in comparison to larger firms. For collateral ($1/collat_t$) we see that medium, large and big firms hold more collateral (0.62) in comparison to smaller firms (0.72). Again this may make smaller firms more prone to adverse shocks as their means to compensate such repercussions are lower.

Variable	Micro	Small	Medium	Large	Big
I_t/K_{t-1}	0.03	0.05	0.05	0.06	0.07
	(0.11)	(0.13)	(0.14)	(0.14)	(0.09)
roi_t	0.03	0.05	0.04	0.03	0.03
	(0.05)	(0.06)	(0.06)	(0.06)	(0.04)
gt_t	0.03	0.02	0.03	0.04	0.04
	(0.13)	(0.12)	(0.13)	(0.13)	(0.12)
$intcf_t$	0.05	0.14	0.14	0.14	0.12
	(0.10)	(0.14)	(0.16)	(0.15)	(0.15)
$1/solvency_t$	6.92	5.59	5.62	5.48	5.67
	(3.61)	(4.53)	(4.19)	(4.49)	(4.26)
$1/liquidity_t$	1.82	3.99	3.14	4.60	8.56
	(70.04)	(40.08)	(39.83)	(40.60)	(35.75)
$lglev_t$	0.78	0.59	0.70	0.71	0.61
	(1.24)	(0.86)	(0.85)	(0.78)	(0.88)
lev_t	1.46	1.54	1.45	1.40	1.20
	(1.37)	(1.59)	(1.50)	(1.23)	(1.62)
$1/collat_t$	0.71	0.73	0.60	0.62	0.64
	(0.19)	(0.23)	(0.21)	(0.21)	(0.23)
$dyndebtshare_t$	0.07	0.05	0.05	0.05	0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
$factor1_t$	0.58	-0.34	0.26	-0.32	0.62
	(1.96)	(1.60)	(2.24)	(2.06)	(2.36)
$factor2_t$	-0.90	-0.92	-1.09	-0.98)	-0.81
	(2.50)	(2.41)	(2.20)	(3.19)	(2.28)

Table 1: Median (standard deviations) of variables used in estimation. Sample: 2006–2012.

[17] It should be noted that the holding of high levels of liquidity does not necessarily reflect financial soundness. It may also be the outcome of restricted investment opportunities resulting in excess liquidity or it could explained by tight lending standards where potential creditors require high liquidity holdings reflecting a firm's creditworthiness.

To obtain some first evidence on the relationship between a firm's accumulation rate and its financial position, we plot investment rates over time according to different levels of creditworthiness. More concrete, we compare the investment rates of firms for which the respective pre-period financial indicator is below the 15th percentiles (denoted by *low*), with firms for which the financial indicator is between the 40th and 60th percentile (*intermediate*) and firms with values above the 85th percentile (*high*).[18] Figure 2 depicts the accumulation rate for each of the balance sheet items considered in this paper, with the only exception of the two common factors. Note, that this is a simple unconditional correlation exercise and has to be interpreted with caution.

As can be seen in Figure 2(a), the accumulation rate is weakly correlated with firms' interest-coverage ratio. There is a temporary downturn of the accumulation rate for firms operating at the lower quantiles in 2010 followed by a quick recovered. Debt has a *dual character*: On the one hand more credit (for given equity), and hence higher leverage, allows firms to invest at higher speed but this debt is also associated with high cash outflows for interest and principal payments which may signal low creditworthiness. Also a firm might have a low leverage either due to high equity or as its access to external credit is restricted. The dual character of debt is partly reflected in the data. The accumulation rate of highly-leveraged firms (see Figure 2(b)) strongly exceeds the ones of the other firms in the pre-crisis period until 2008. However, the GFC let to a more severe downturn in the accumulation rate of highly leveraged firms in comparison to the remaining companies in the following two years. This may support the perspective that lenders applied more strict lending standards making it harder for firms with a debt-overhang to obtain credit at all or at least at reasonable conditions. The investment ratio of low- and medium-leveraged firms is found being much smoother during the crisis-episode. For both low and medium leveraged firms no adverse repercussions on investment rates can be observed; their rates are actually increasing.

In Figure 2(f) the investment dynamics for firms grouped according to the dynamic debt share are depicted. Firms with low levels of dynamic debt share experienced the highest accumulation rates over the entire period on average. For firms with medium levels one can observe a smooth investment path instead but the associated rate is slightly lower over time. Firms with a high dynamic debt share had on average the highest investment rates until 2009 before their investment activities massively declined. Hence, the data suggest an inverse but weak relationship between the level of dynamic debt and a firm's accumulation rate. Grouping firms according to their collateral rates, $1/collat$, shows that the firms with the lowers collateral also exhibit the least

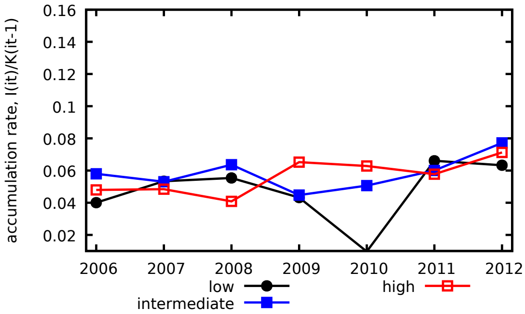
[18] For a more detailed country-wise analysis of the impact of the recent GFC on fixed-investment see ECB (2013, p. 60ff.).

investment rates over time (see Figure 2(d)). This is at least visible since 2009 even though these firms had similar investment rates as the more financially solid counterparts. Again, this suggest that since the GFC potential lenders have tightened their lending standards which affected firms with low collateral holdings adversely. Using solvency as a sample-splitting variable indicates no differences in the accumulation rate of firms with intermediate and high solvency rates, as depicted in Figure 2(e). Their investment paths are very smooth and the GFC had no adverse repercussions. The investment dynamics of the least solvent firms are in contrast much more volatile over time, and one can observe a temporary decline in the investment rate in 2010 here. A firm's liquidity position does not seem to be correlated with their accumulation rate as displayed in Figure 2(g). This may be explained by different reasons high liquidity holdings may imply, as argued before. Lastly, one can see a clear hierarchy between a firm's cash flow rate and its investments, as displayed in Figure 2(h). There is a strong positive correlation between the cash flow rate and investment rate.

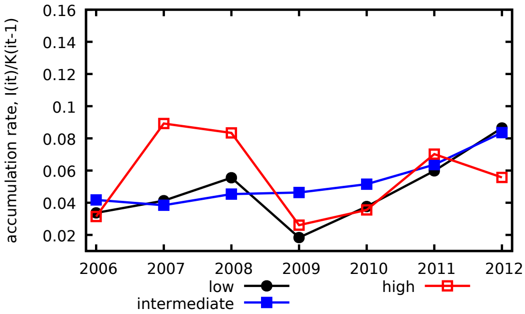
Overall, this simple graphical description provides some initial evidence for an existing link between a firm's financial position and its investment rates. However, the link cannot be observed for all financial indicators. Furthermore, there maybe non-linear relationships between financial pressure and fixed-investment growth which is in line with recent findings on the Euro area firm-level (ECB, 2013, p. 59). This may be explained by the dual character of debt, enhancing potential growth on the one hand but also leading to higher debt burdens accompanied by higher real debt servicing costs on the other hand. This nonlinear relationship is partly reflected in our estimation results as will be shown in the following.

4 Econometric results

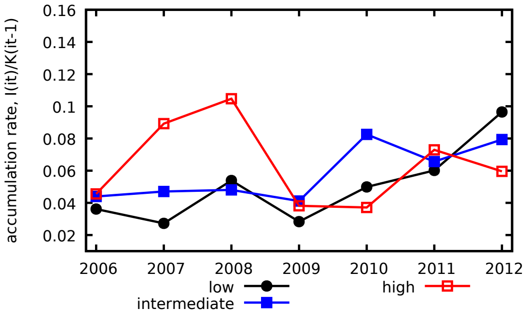
In this section the estimation results for both the linear model (eq. (1)) as well as the threshold model (eq. (2)) are presented and discussed. The investment functions are estimated for nine different specifications which deviate in terms of the underlying threshold variable D. The first step of the analysis involves the determination of the number of thresholds (and hence regimes). We check whether a linear model fits the data sufficiently well or whether any threshold effects exist. For all specifications, we test for up to two (three) thresholds (regimes). After having determined the threshold values and having tested for their significance, the actual estimation of the regime-dependent as well as -independent parameters follows. The benchmark specification is a linear fixed-effects model with no thresholds. This functional form corresponds to the benchmark model applied in many previous studies.



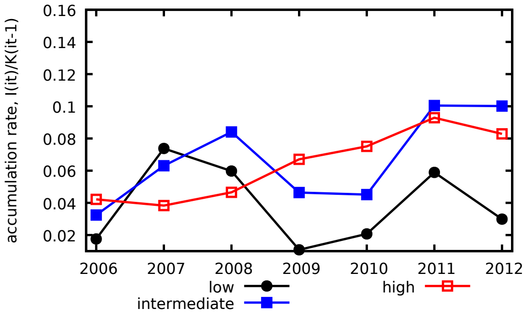
(a) Interest coverage ratio: $intcf$



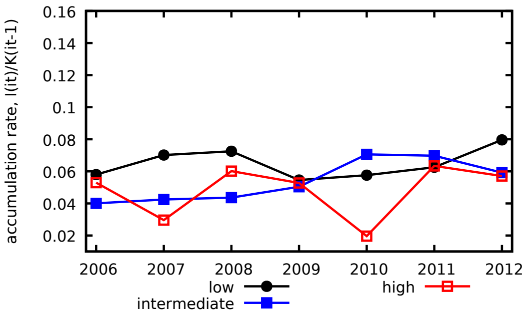
(b) Total liability to total equity ratio: lev



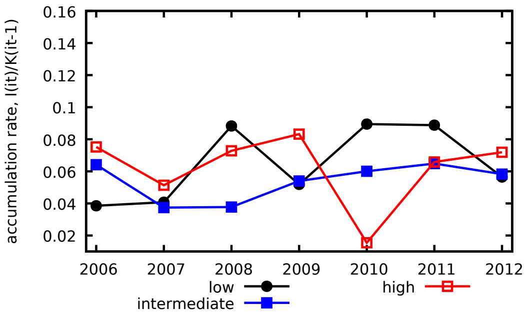
(c) Total long-term liability to total equity ratio: $lglev$



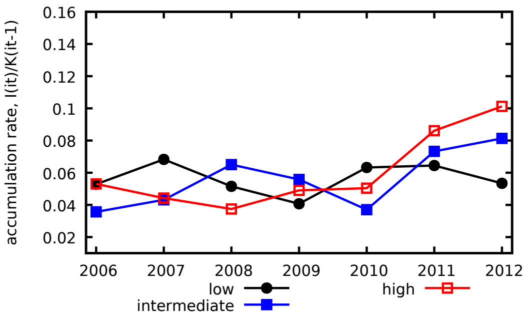
(d) Inverse of collateral: $1/collat$



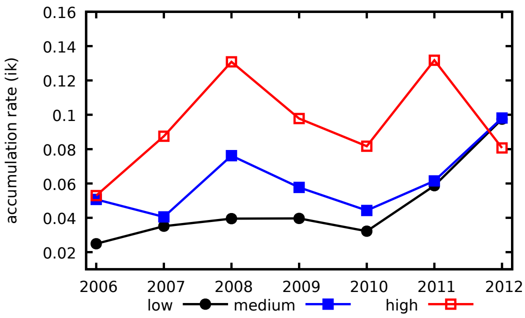
(e) Inverse of cash flow to total liability: $1/solvency$



(f) Dynamic debt share: $dyndebtshare$



(g) Inverse of cash at hand over short-term liability: $1/liquidity$



(h) Cash flow rate: cf

Notes: For each of the financial indicators considered, the charts show the current median accumulation rate ($ik_{it} = \frac{I_{it}}{K_{it-1}}$) for firms for which this (one-period lagged) indicator shows a *high* value (above the 85th percentile), an *intermediate* value (between the 40th and 60th percentiles) and a *low* value (below the 15th percentile).

Figure 2: Time series of the accumulation rate according to financial position. Sample: 2006–2012.

4.1 Estimation results and cash flow sensitivity of investments

First the linear model results are reported. In the first part of Table 3 the cash flow sensitivities of investment using the linear benchmark model are reported for all nine specifications. The respective linear coefficient estimate is denoted by β^{cf}_{Lin}. Irrespective of the considered balance sheet variable D_{it-1}, we find for all nine linear specifications positive and significant (at the 1% level) point estimates ranging from 0.128 to 0.441. This directs attention to existing financial constraints firms in Germany face, even though we haven't split the sample into some categories at this stage. Nevertheless, these results confirm previous findings as described before. However, it should be noted that the estimates are biased and inefficient in case the true data generating process is nonlinear.

Next, we test for nonlinear threshold effects for which the results are reported in Table 2. The first column displays the name of the respective threshold variable D_{it-1} applied as outlined in eq. (2). The testing sequence starts with the null hypothesis of no threshold against a single threshold ($H_0 : T = 0$ vs. $H_1 : T = 1$). If the null is rejected, one proceeds by testing the null of a single threshold against two thresholds ($H_0 : T = 1$ vs. $H_1 : T = 2$). The second column computes the respective bootstrap p-value, and the last two columns tabulate the point estimates (plus 95% confidence intervals) of the threshold value(s), γ. In case more than one threshold is found, the refinement values of γ are provided.

For four specifications evidence of regime-dependency is found. The specifications for which thresholds effects are found separately include leverage (lev_{it-1}), the inverse solvency measure ($1/solvency_{it-1}$), the inverse liquidity measure ($1/liquidity_{it-1}$) and the dynamic debt share ($dyndebtshare_{it-1}$). Using $1/solvency_{it-1}$ as a threshold variable, we find evidence for two thresholds (each significant at the 1% level) and a single threshold for the lev_{it-1} (significant at the 5% level), $dyndebtshare_{it-1}$ (significant at the 1% level) and $1/liquidity_{it-1}$ (significant at the 5% level), respectively. Hence, at least for these four specifications a linear model results in biased estimates of cash flow on investment.

Threshold Variable $D:$	p-value	γ_1	γ_2
Interest coverage ratio: $intcf_{it-1}$			
$H_0: T=0$ vs. $H_1: T=1$	0.229	0.064	
		(-0.005|0.370)	
$H_0: T=1$ vs. $H_1: T=2$	0.219	0.064	0.252
		(-0.005|0.370)	(0.054|0.254)
Inverse of cash flow to total liability: $1/solvency_{it-1}$			
$H_0: T=0$ vs. $H_1: T=1$	0.002	4.187	
		(4.030|4.187)	
$H_0: T=1$ vs. $H_1: T=2$	0.000	4.187	4.301
		(4.030|4.187)	(4.301|4.314)
Inverse of cash at hand over short-term liability: $1/liquidity_{it-1}$			
$H_0: T=0$ vs. $H_1: T=1$	0.011	13.633	
		(11.494|17.177)	
$H_0: T=1$ vs. $H_1: T=2$	0.289	13.633	0.627
		(11.494|17.177)	(0.466|61.691)
Total long-term liability to total equity: $lglev_{it-1}$			
$H_0: T=0$ vs. $H_1: T=1$	0.133	0.298	
		(0.252|1.937)	
$H_0: T=1$ vs. $H_1: T=2$	0.163	0.298	1.824
		(0.252|1.937)	(0.621|1.937)
Total liability to total equity: lev_{it-1}			
$H_0: T=0$ vs. $H_1: T=1$	0.033	1.145	
		(0.670|1.893)	
$H_0: T=1$ vs. $H_1: T=2$	0.177	1.145	2.843
		(0.670|1.893)	(0.670|3.246)
Inverse of collateral: $1/collat_{it-1}$			
$H_0: T=0$ vs. $H_1: T=1$	0.199	0.358	
		(0.349|0.402)	
$H_0: T=1$ vs. $H_1: T=2$	0.618	0.358	0.317
		(0.349|0.402)	(0.280|0.946)
Dynamic debt share: $dyndebtshare_{it-1}$			
$H_0: T=0$ vs. $H_1: T=1$	0.005	0.041	
		(0.041|0.045)	
$H_0: T=1$ vs. $H_1: T=2$	0.167	0.041	0.129
		(0.041|0.045)	(0.014|0.131)
Inverse of 1st common factor: $1/factor1_{it-1}$			
$H_0: T=0$ vs. $H_1: T=1$	0.481	0.436	
		(-3.117|2.385)	
$H_0: T=1$ vs. $H_1: T=2$	0.101	0.436	0.468
		(-3.117|2.385)	(0.468|0.468)
Inverse of 2nd common factor: $1/factor2_{it-1}$			
$H_0: T=0$ vs. $H_1: T=1$	0.793	0.709	
		(-4.782|3.096)	
$H_0: T=1$ vs. $H_1: T=2$	0.004	0.709	0.766
		(-4.782|3.096)	(0.749|0.769)

NOTE: The test results for multiple thresholds are provided. $T0$ vs. $T1$ and $T1$ vs. $T2$ refer to the null hypotheses of a linear model against a single threshold model (2 regimes) and a single threshold against a double threshold model. We provide the bootstrap p-values based on 999 replications. γ_1 and γ_2 denote the estimated threshold values (in square brackets the 95 pct. CIs are provided). For the test on two threshold, the refinement estimates are reported. The number of quantiles checked is 300.

Table 2: Threshold Test Results. Sample: 2006 to 2012.

Threshold Variable D**:**	$intcf_{t-1}$	$1/solvency_{t-1}$	$1/liquidity_{t-1}$	$lglev_{t-1}$	lev_{t-1}	$1/collat_{t-1}$	$dyndebtshare_{t-1}$	$1/factor1_{t-1}$	$1/factor2_{t-1}$
Linear benchmark coefficients									
β^{cf}_{Lin}	0.217***	0.193***	0.128***	0.182***	0.172***	0.173***	0.235***	0.441***	0.409***
	(0.055)	(0.045)	(0.045)	(0.048)	(0.048)	(0.047)	(0.057)	(0.160)	(0.129)
SSE	11.003	11.839	11.200	12.519	12.999	12.314	10.970	3.024	2.279
Regime-dependent coefficient estimates									
β^{cf}_{Low}		0.155***	0.083**		0.101*		0.182***		
		(0.044)	(0.039)		(0.052)		(0.059)		
β^{cf}_{Middle}		0.665***	0.208***		0.208***		0.304***		
		(0.103)	(0.046)		(0.046)		(0.055)		
β^{cf}_{High}		0.262***							
		(0.051)							
SSE		11.336	10.994		12.830		10.779		
T	6	6	6	6	6	6	6	6	6
N	234	245	220	251	268	257	214	60	67

NOTE: The depending variable refers to the investment rate, $\frac{I_{it}}{K_{it-1}}$. The β^{cf}_{Lin} coefficient is based on the corresponding linear FE panel model. The threshold variables *intcf*, *solvency*, *liquidity*, *lglev*, *lev*, *collat dyndebtshare*, *factor*1 and *factor*2 refer to the interest coverage ratio, cash-flow-to-debt ratio, cash-to-short-term-debt ratio, long-term-debt-to-equity ratio, total-debt-to-equity ratio, collateral, dynamic debt share, and two extracted principal components, respectively. In case more than one significant threshold is significant at least at the 10 pct. level, the refinement coefficients are reported. $***$, $**$ and $*$ indicate significance at the 1 pct., 5 pct. and 10 pct. level. White standard errors are given in parentheses.

Table 3: Coefficient Estimates of the Cash Flow Rate on the Investment Rate using the Linear Benchmark Model and Threshold Model. Sample: 2006 to 2012.

We report and discuss the regime-dependent coefficient estimates only for the four specifications for which significant threshold effects were found. The regime-dependent coefficients are denoted by β^{cf}_{Low}, β^{cf}_{Middle} and β^{cf}_{High}, respectively, and are reported in Table 3. The abbreviations refer to the marginal effect of the cash flow rate on the fixed investment rate for firms with low, intermediate and high values of the respective threshold variable (in case three regimes are detected). The regimes are separated by the estimated threshold value γ, as reported before in Table 2.

The estimated threshold values for the $1/solvency$ measure are close to each other, having values of $\gamma_1 = 4.187$ and $\gamma_2 = 4.301$, respectively. The empirical median value of $1/solvency$ is 6.9 for micro firms and about 5.6 for the remaining companies. Thus the a majority of firms in our sample belong to the rather fragile regime according to this financial measure. The cash flow sensitivity is lowest for firms with the highest solvency measure ($1/solvency \leq 4.187$) with a coefficient of $C^{cf}_{Low} = 0.155$ (significant at the 1% level) as reported in Table 3. This point estimate is close to the linear benchmark coefficient $\beta^{CF}_{Lin} = 0.193$. For the intermediate regime ($4.187 < 1/solvency \leq 4.301$) the cash flow sensitivity increases to $C^{cf}_{Middle} = 0.665$ (significant at the 1% level) and indicates much tighter financial constraints for firms falling into this regime. Surprisingly we find for firms operating in the regime with the lowest solvency rates ($1/solvency > 4.301$) still a high cash flow coefficient $C^{cf}_{High} = 0.262$ (significant at the 1% level) but which is much lower compared to firms in the intermediate state. Still, the effect is almost twice as high as for firms operating in the least restrictive financial regime. This seemingly counterintuitive result may be explained as follows: A low level of *solvency* does not necessarily go hand in hand with (expected) high default risk if existing debt is sufficiently secured by existing collateral. Table 2 reports the median collateral holdings of firms falling into a specific regime. The statistics indicate that the most solvent firms hold higher collateral rates ($1/collateral = 0.63$) while the firms falling into the intermediate regime, characterized by the tightest financial constraints, hold the least collateral rates ($1/collateral = 0.7$). The least solvent firms are, however, characterized by higher collateral holdings ($1/collateral = 0.68$) as the ones in the intermediate state which may explain why the cash flow sensitivity of these companies is lower. Thus, the tight financial restrictions firms in the intermediate regime face, potentially result (conditional on $1/solvency$) from rather low levels of collateral available to secure their debt commitments. Creditors consciously prefer to secure their credits by collateral, and hence collateral comprises additional key information on financial constraints.

Figure 3 depicts the share of firms for each size class falling into a specific financial regime over time.[19] Until 2007 all micro firms operated in the low-solvency regime ($1/solvency > 4.301$) (see Figure 3(a)). However, since 2008 the share of micro firms falling either into the medium- or high-solvency regime has had increased to about 20% before decreasing again in 2012. In contrast about 30% to 40% of all SMEs and larger firms operate at least in the intermediate solvency-state. This result suggests that the probability to fall into a financially sound regime is lower for micro firms in comparison to larger companies. Furthermore, small firms have caught up in terms of solvency and stabilized their balance-sheets since 2008. Improved solvency rates could be a consequence of increased lending standards creditors demanded after the GFC. In total, the repercussions of the GFC on the solvency situation of firms seems to be modest, and the correlation between the probability to stay in a specific regime and firm size is rather weak, at least for SMEs and larger companies.

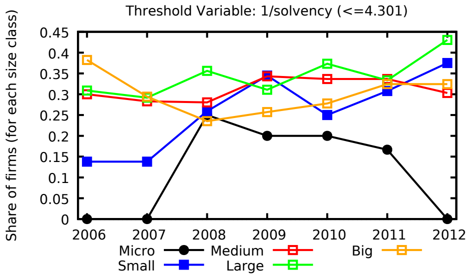
Financial regime	$1/solvency_t$	$1/liquidity_t$	lev_t	$dyndebtshare_t$
Low	0.63	0.64	0.65	0.62
	(0.24)	(0.24)	(0.25)	(0.23)
Middle	0.70	0.71	0.65	0.69
	(0.20)	(0.25)	(0.25)	(0.25)
High	0.68			
	(0.24)			

NOTE: The first column indicates the respective financial regime firms operate in, as estimated and reported in Table 2. The following three columns report the firms' median value (standard deviation in brackets) of collateral holdings ($1/collateral$) for each specific regime.

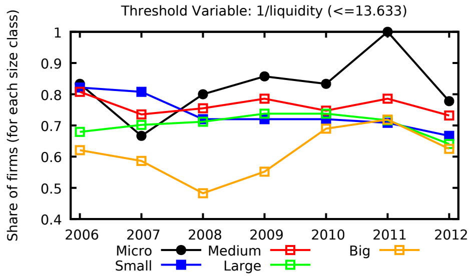
Table 4: Median (standard deviation) collateral holdings according to the estimated regimes. Sample: 2006–2012.

Using the threshold variable $1/liquidity$ reveals one significant threshold at $\gamma = 13.633$. The median value of $1/liquidity$ was found being 1.82 for micro firms and 8.56 for large firms implying that the threshold value separates liquid from rather illiquid companies from each other. According to the estimation results (see Table 3), the investment rate of firms with high liquidity holdings ($1/liquiidity \leq 13.633$) reacts less sensitive to changes in the cash flow rate ($\beta^{CF}_{Low} = 0.083$ and significant at the 1% level) in comparison to firms operating in the financially constrained regime for which $\beta^{CF}_{Middle} = 0.208$ (significant at the 1% level). Again we find a correlation with firms' collateral holdings and their regime belonging: The most liquid firms facing the least intense financial constraints are again holding higher collateral rates ($1/collateral = 0.64$) compared to financially constrained companies ($1/collateral = 0.71$). Figure 3(b) depicts that about 60% of all big firms operate in the high-liquidity regime. The fraction is slightly higher

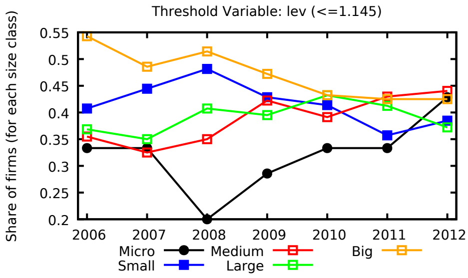
[19]Find the corresponding plots for the remaining variables in the Appendix in Figure 4.



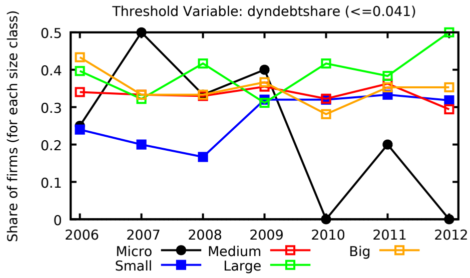
(a) Inverse of cash flow to total liability: $1/solvency$



(b) Inverse of cash at hand over short-term liability: $1/liquidity$



(c) Total liability to total equity ratio: lev



(d) Dynamic debt share: $dyndebtshare$

Figure 3: Share of firms for each size class separately falling below an estimated threshold over time. Sample: 2006–2012.

for the remaining firms and ranges between 70% and 85%. Again, there is only weak evidence that firm size matters for the probability to stay in the high-liquidity regime. The GFC has not been accompanied by a substantial change in the relative shares of firms over time. In total, this may suggest that the recent GFC had no meaningful effect on firms' liquidity holdings in Germany and let to no considerable switches of firms from a financially solid to a fragile regime which confirms our previous description of the data.

Using leverage (lev) as a threshold variable in the specification reveals a kink at a value of 1.145, just below the median for most companies which ranges between 1.2 and 1.54. Again the results are striking: The cash flow sensitivity of low-leveraged firms ($lev \leq 1.145$) is only $\beta^{CF}_{Low} = 0.101$ (significant at the 10% level) but twice that high for highly leveraged firms with a coefficient of $\beta^{CF}_{Middle} = 0.208$ (significant at the 1% level). Hence, the latter category of companies faces tighter financial constraints relative to financially more solid ones. Interestingly, this time we do not find evidence that collateral rates help to explain the regime belonging of firms as the corresponding value is $1/collateral = 0.65$ for companies in both regimes. About 50% of all big firms operate in the low-leverage regime but the share is slightly lower for SMEs and large firms ranging between 35% and 45% (see Figure 3(c)). Again, the GFC was not accompanied by a systematic switch of firms towards the high-leverage regime. The picture again looks different for micro firms: In 2008 the share of micro firms in the low-leverage regime fell from 35% to 20% before these companies were able to de-leverage again, improving their financial position.

The overall picture remains valid using the dynamic debt share as a potential threshold variable. We find a single significant threshold at $\gamma_1 = 0.041$ separating lowly indebted from highly indebted companies. The median value of *dyndebtshare* ranges from 0.05 to 0.07. For firms operating in the low-debt regime, we find a cash flow sensitivity of about $\beta^{CF}_{Low} = 0.181$ but a much higher one for firms in the high-debt regime, $\beta^{CF}_{Middle} = 0.304$ (both significant at the 1% level). Furthermore, the least constraint firms hold higher collateral rates ($1/collateral = 0.62$) as the constrained ones ($1/collateral = 0.69$). About 35% to 45% of all medium-sized, large and big companies operate in the low-debt regime, as depicted by Figure 3(d). Between 2006 and 2008 only 20% of all small companies were located in the low-debt regime, but the fraction has increased to 30% since 2009 suggesting some deleveraging process for these units. The corresponding share of micro firms fluctuates between 25% and 40% between 2006 and 2009 before the fraction has substantially declined since then. This indicates that SMEs and larger firms were able to compensate the adverse effects of GFC much better in comparison to micro firms which had to increase their dynamic debt shares, such that many micro firms switched out of the low-debt regime into the high-debt regime.

Overall, we find strong evidence that firms in Germany face financial constraints. Furthermore, the results indicate a specific regime dependency saying that the degree of financial constraintness is much more intense for firms with weak balance sheets. Additionally, these financially constrained firms are characterized by rather low levels of collateral. However, firm size, as often argued, does not play a prominent role even though it cannot be fully neglected. The latter aspect supports the findings of Martinez-Carrascal and Ferrando (2008) who also do not find evidence that firm size matters for the degree of financial restrictions firms face. According to our estimation, an exception may be micro firms for which we find, in comparison to larger companies. In comparison, a higher fraction of micro firms holds rather high levels of liquidity (probably reflecting tight lending standards applied), are more frequently belonging to the high-leverage regime and are rather characterized by low levels of solvency. Nonetheless, the results should be seen with caution as the number of micro firms in our sample is relatively low with only about 10 cross-sectional units.

Regime-independent coefficient estimates Lastly, we briefly present the estimation results of the regime-independent coefficients which are provided in Table 5. For most specifications we find a negative effect of the number of workers (in logs) on capital accumulation. Growth of real sales revenue is not statistically significant in any of the models. Real return on investment seems to be positively but concavely related to capital accumulation. The effect of the depreciation rate, d, is always positive, but there is also evidence for a concave relationship between d and the investment rate. This is in line with the findings of the Bundesbank showing that deduction is a major source of internal funding for firms (Bundesbank, 2012). The great financial crisis is accompanied by a significant positive level shift in the investment rate. Additionally, the interaction term $gfc * w$ indicates that the effect of the GFC on capital accumulation increases in firm size measured by the (log) number of workers. Hence, larger firms were better able to cope with the repercussions of the economic crisis in comparison to smaller firms. Furthermore, firm-level investment is contemporaneously and pro-cyclically related to the output gap, gdp.

However, most interestingly there is only weak evidence for a relationship between capital accumulation and the lagged level of the respective threshold variable. Only for the interest coverage ratio ($intcf$), the dynamic debt share ($dyndebtshare$) and the second common factor ($factor2$) a significant (at least at the 10% level) effect is found. The level of the interest coverage ratio is negatively related to the investment rate while the two other effects are positive. This mirrors the dual character of debt, as argued before. Overall, this result highlights an additional channel through which financial conditions may affect realized investments: The status of the balance-sheet not only has indirect effects on investments by providing signals of creditworthiness but may also affect the accumulation rate by e.g. restricting the amount of available internal funds. However, to be a valid finding this potential channel needs to be analyzed in more detail in future research.

Threshold Variable D:	$intcf_{t-1}$	$1/solvency_{t-1}$	$1/liquidity_{t-1}$	$lglev_{t-1}$	lev_{t-1}	$1/collat_{t-1}$	$dyndebtshare_{t-1}$	$1/factor1_{t-1}$	$1/factor2_{t-1}$
$const$	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.005)
w_{t-1}	-0.111^{**}	-0.088^{**}	-0.094^{**}	-0.113^{**}	-0.096^{**}	-0.108^{**}	-0.104^{**}	-0.062	-0.085
	(0.044)	(0.044)	(0.044)	(0.043)	(0.040)	(0.042)	(0.051)	(0.055)	(0.056)
gt_{t-1}	0.007	-0.001	0.017	-0.009	0.002	0.019	0.017	-0.026	0.027
	(0.024)	(0.023)	(0.023)	(0.023)	(0.022)	(0.020)	(0.024)	(0.043)	(0.034)
roi_{t-1}	0.439^{*}	1.026^{***}	0.362	0.426^{*}	0.401^{*}	0.512^{**}	0.710^{***}	0.033	0.097
	(0.244)	(0.240)	(0.238)	(0.225)	(0.214)	(0.201)	(0.260)	(0.442)	(0.392)
roi^2_{t-1}	-3.020^{***}	-3.447^{***}	-0.636	-2.770^{**}	-1.941^{*}	-2.764^{***}	-3.402^{***}	-2.658	-4.385^{**}
	(1.039)	(1.095)	(1.246)	(1.069)	(1.032)	(0.947)	(1.284)	(2.562)	(2.197)
d_t	6.946^{***}	9.472^{***}	9.075^{***}	9.670^{***}	8.067^{***}	8.856^{***}	8.546^{***}	24.206^{***}	15.257^{***}
	(2.181)	(2.258)	(2.244)	(2.151)	(1.876)	(1.983)	(2.319)	(4.753)	(2.829)
d^2_t	-10.443	-23.493	-25.304	-24.241	-12.364	-26.735^{*}	-17.881	-153.150^{***}	-79.653^{***}
	(16.428)	(17.356)	(17.769)	(16.747)	(14.509)	(15.434)	(17.790)	(37.595)	(19.574)
gfc	0.024^{**}	0.035^{***}	0.026^{**}	0.023^{**}	0.022^{**}	0.025^{***}	0.025^{**}	-0.013	0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)	(0.020)	(0.016)
$gfc_t * w_t$	0.053^{**}	0.076^{***}	0.022	0.043^{**}	0.044^{**}	0.044^{**}	0.052^{**}	0.108^{**}	0.140^{***}
	(0.021)	(0.021)	(0.021)	(0.019)	(0.019)	(0.018)	(0.022)	(0.050)	(0.035)
gdp_t	0.005^{***}	0.005^{***}	0.003^{**}	0.003^{**}	0.004^{***}	0.004^{***}	0.004^{**}	0.003	0.004
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
D_{t-1}	0.071	0.006	-0.000	-0.006	-0.023	-0.215	-0.501	0.001	0.005
	(0.084)	(0.005)	(0.000)	(0.018)	(0.016)	(0.198)	(0.353)	(0.004)	(0.005)
D^2_{t-1}	-0.233^{*}	-0.000	0.000	0.002	0.000	-0.039	3.816^{**}	0.000	0.002^{**}
	(0.125)	(0.000)	(0.000)	(0.004)	(0.002)	(0.160)	(1.839)	(0.001)	(0.001)
T	6	6	6	6	6	6	6	6	6
N	234	245	220	251	268	257	214	60	67

NOTE: w, gt, d, gdp and D refer to the the number of workers (in logs), growth of real sales revenues, depreciation rate, the output gap and the threshold variable, respectively. $***$, $**$ and $*$ indicate significance at the 1 pct., 5 pct. and 10 pct. level. White standard errors are given in parentheses.

Table 5: Coefficient Estimates of the Regime-independent Variables. Sample: 2006 to 2012.

4.2 A word of caution

A critical point in estimating reduced-form fixed-investment functions concerns the issue of controlling for demand effects. One issue refers to the question whether Tobin's q or growth in sale revenues fully capture demand effects. If this identification issue remains unsolved, it is unclear whether the positive cash flow effect stems from a shift on the demand side or whether it has its causes in increased capital market imperfections emerging from the supply side. Hence, for identification one needs to make sure that the control variables fully capture shifts in demand in order to interpret the marginal effect of cash flow as reflecting supply side factors.

In their, unfortunately, less known paper Fazzari and Petersen (1993) have suggested an extension of their initially proposed estimation approach. The authors emphasize the dual role of working capital as a *use of funds* as well as a *source of liquidity.*[20] The authors start their argument by computing the correlation between working capital and fixed-investment. As working capital behaves pro-cyclically and is positively correlated with sales and profits, the inclusion of working capital into the fixed-investment function should result in a positive effect on fixed-investment. However, this only holds true if working capital as a use of funds does not compete with fixed-investment under a binding financial constraint. Thus, for firms facing imperfect capital markets, the marginal effect of working capital is expected to be negative.

Secondly, Fazzari and Petersen claim that the standard reduced-form fixed-investment model underestimates the full effect of capital market imperfections. They argue that the coefficients estimated only reflect an "*…average 'short-run' impact of cash flow shocks, after the firm engages in optimal investment smoothing*" (Fazzari and Petersen, 1993, p. 329). In order to fully capture financing constraints one has to control for endogenous changes in working capital as a source of fund mitigating cash flow shocks. If one does not control for working capital in the fixed-investment function, one cannot rule out that e.g. negative cash flow shocks are compensated by the liquidity working-capital provides (especially cash holdings). If a firm holds a large stock of working capital, the negative cash flow shock may be compensated. However, the same shock will have a much larger impact on investment if the stock of working capital is small and does not allow to smooth investment plans. Under this argumentation, the previously reported results, due to the non-consideration of working capital in our investment function, may only capture the very short-run cash-flow-to-fixed-investment sensitivity but not the long-run effects. In Fazzari and Petersen's study the marginal effect of cash flow on fixed-investment is found being indeed

[20] Working capital is defined as the difference between short-term assets comprising accounts receivable, inventories and cash, minus the sum of accounts payable plus short-term debt.

three to four times higher after considering working-capital as an additional regressor.

Unfortunately, the DAFNE dataset includes a high number of missing observations for working capital. However, we estimated linear benchmark models including the contemporaneous effect of working capital as an additional regressor. Overall its point estimate was found being significant and positive. Surprisingly, the effect on the cash flow sensitivity was rather negligible. These results are not reported here as the number of observations is too small to be sufficiently reliable. This short paragraph is added to outline remaining limitation of our own work and of others on measuring financial investment constraints.

Another aspect concerns the substitution effect. The financing instruments a firm can choose, include among others equity, bank loans, debt securities, inter-company loans, trade credit facilities or informal loans. Thus, firms are to some degree flexible in their financing strategies. However, it should be kept in mind that this flexibility is rather limited for typically informationally opaque SMEs. On the aggregate level there is evidence that in some Euro area countries corporations have replaced bank loans with market-based funding instruments such as equity and debt securities, trade credit as well as intra-sectoral financing between firms (ECB, 2013, p. 21ff.).[21] A strong substitution channel may mitigate the relevance of financial frictions stemming from bank credits. However, to control for substitution effects is demanding as an appropriate model requires a multivariate or instrumental variable set-up in order to control for endogeneity issues.

Lastly one should mention the potential repercussions of the recent financial crisis on the estimation results. It might be the case that the relationships between the variables have changed as a result of deeper structural changes due to the GFC. In this article we have dealt with this issue by including a simple shift dummy which accounts for possible changes in the conditional mean of the accumulation rate, as well as an interaction term between the shift dummy and the (log) number of workers. The latter regressor controls for differences in the repercussions of the GFC depending on firm size. This may be justified for two reasons: First, the article is about the relationship between realized firm investment, cash flow and balance sheet aspects. Thus, the GFC, captured in the data, may even provide information on rare events which helps us to identify specific regimes. Second, as the time span covered is rather small, it is difficult to detect parameter changes due to breaks over time using the econometric model applied. Nevertheless, the question of how the GFC might have impacted on the relationships between investment, cash flow and balance sheet measures is definitely of importance but should be addressed in another

[21] See also Casey and O'Toole (2013) for empirical evidence on the use of alternative sources of finance by European SMEs during the financial crisis.

paper using a longer time span.

5 Policy Implications and Summary

This article has shown that a firm's financial situation matters. In particular, it has linked firms' balance-sheet positions to fixed capital accumulation. The paper contributes to the literature on financial investment constraints which has gained renewed interest during the recent financial crisis (IMF, 2015). The results from the estimation of investment functions reveal a significant and positive effect of cash flow on fixed-investment. This confirms major previous findings in the literature. Additionally, there is evidence that the cash-flow-investment nexus is regime-dependent as the marginal effect of cash flow on capital accumulation is lower for financially solid firms in comparison to fragile ones. The differences in the magnitude are substantial for some specifications. Neglecting those nonlinearities results in biased coefficient estimates and underrates the relevance of financial constraints firms face.

In contrast to standard contentions, we find only limited evidence that firm size is a relevant variable to discriminate between financially constrained and unconstrained companies. It is argued that balance sheet indicators are more appropriate to separate firms accordingly. The only exception are micro firms for which the probability to fall into a financial constrained regime is found being higher in comparison to other size classes. During the recent financial crisis period, a considerable share of micro firms switched from a solid financial state to a fragile one. This suggests that micro firms were hit hardest by the recent downturn. Our results clearly stress that a symmetric macro-wide shock such as the recent financial crisis may have asymmetric repercussions across heterogeneous firms.

Our findings help to explain the persistence of low investment growth in Germany over the past decade. There is direct evidence that stresses the role of financial frictions in restricting the availability of credit to firms (Hall, 2011; Stock and Watson, 2012). This channel may also explain the long-lasting weak labor market development in Germany at the beginning of the 2000s, as restricted access to credit may result in persistent insufficient aggregate demand and forces firms to purge excess labor. Chodorow-Reich (2013) has recently studied the link between the health of a firm's lenders and a firm's employment outcomes, and finds an economically important relationship.

As statistical numbers indicate, German firms were on average less indebted (according to standard balance-sheet measures) compared to firms e.g. in Italy, Spain, Greece or Portugal before the GFC. Thus, the share of firms falling into the financially fragile regime is rather low in Germany. However, this may be different for economies in the periphery, and helps to explain why the "deleveraging-aggregate demand" channel recently emphasized by Mian and Sufi (2010) is less prevalent in Germany in comparison to other crisis countries. As firms and households face high debt burdens and restricted access to external finance, they are forced to de-leverage which has severe negative repercussions on aggregate demand (Biggs et al., 2010; Keen, 2010; Eggertsson and Krugman, 2012; Mian et al., 2013). These links also help to point out why the downturn accelerated in 2008 much stronger in these southern European economies in comparison to Germany. Furthermore, it also provides an explanation of why the negative economic repercussions of the GFC were rather limited in Germany in the period after 2008.

Finally, the finding that the financial regime a firm operates in does not depend on firm size may highlight the working of relationship-banking in Germany. The literature suggests that relationship-banking still plays a prominent role in Germany (Memmel et al., 2008). SMEs typically hold long-term relationships with a single or a small number of banks which are mostly public non-profit maximizing institutions. Relationship-lending can be a meaningful institutional device to mitigate the impact of unforeseen events and/or asymmetric information problems on credit lending (Gobbi and Sette, 2012). A bank-based system with widespread relationship-banking characteristics may explain, why for German SMEs the degree of financial constraintness in terms of access to external funds is rather low over the business cycle. Unfortunately, data constraints limit further investigation on this issue but future research should put a focus on whether relationship-banking aspects help to resolve the weak correlation between firm size and the degree of financial frictions in Germany.

The implications for economic policy can be briefly summarized as follows: Stimulating aggregate demand may foster firm-level investments, but is most likely not sufficient. According to the results, corporate indebtedness impedes investment, and thus economic policy must find instruments to deal with excessive debt and non-performing loans. Furthermore, policies should be aimed at improving the access to capital at lower costs.

Data Appendix

The list of industrial sectors considered is provided in Table 6 below.

Industrial sectors included
Mining and quarrying
Manufacturing
Electricity, gas, steam and air conditioning supply
Water supply, sewerage, waste management and remediation act
Construction
Wholesale and retail trade; repair; repair of motor vehicles and motorcycles
Transportation and storage
Accommodation and food service activities
Information and communication

Table 6: Overview of industries considered in the dataset

Variable definition and sources All data are taken from the Creditreform DAFNE database, as long as not differently stated.

Investment to capital stock ratio, $ik_{i,t} = \frac{\Delta K_{i,t}}{K_{i,t-1}} = \frac{I_{i,t}}{K_{i,t-1}}$, is the ratio of the change in tangible fixed assets over tangible fixed assets of the previous period. Tangible fixed assets consists of land, property, plant and equipment.

Cash flow over tangible fixed assets, $cf_{i,t} = \frac{Cf_{i,t}}{K_{,t-1}}$, is the ratio of profits after taxes and interest over tangible fixed assets of the previous period.

Depreciation on fixed assets over tangible fixed assets, $d_{i,t} = \frac{DP_{i,t}}{K_{,t-1}}$. The depreciation on fixed assets had to be imputed due to missing values for all units calculating it alternatively by: depreciation on total assets weighted by the ratio of tangible fixed assets to total assets. This approach closely follows Engel and Middendorf (2009).

Real return on investment $roi_{i,t}$ is the nominal return on investment minus GDP price level inflation rate (AMECO: PVGD).

Growth of real sales revenue, $gt_{i,t}$, where nominal sales revenue is deflated by GDP price level (AMECO: PVGD).

Log of the number of workers per firm, $w_{i,t}$.

Total liabilities to total equity ratio, $lev_{i,t}$.

Total liabilities minus short-term liabilities (maturity up to one year) to total equity ratio, $lglev_{i,t}$.

Interest coverage ratio, $intcf_{i,t}$, equals interest expenditures minus interest income to cash flow ratio, $intcf_{i,t} = \frac{Int_{i,t}}{Cf_{,t}}$

Solvency measures the cash flow to total liability ratio, $solvency_{i,t}$.

Collateral equals the sum of total inventory stock, tangible assets plus cash available at hand or at bank, over total tangible assets, $collat_{i,t}$.

Liquidity is the ratio of cash at hand over short-term debt, $liquidity_{i,t}$.

Real GDP output gap, gdp_t, (AMECO: AVGDGP).

Great Financial Crisis, gfc_t, is dummy variable which takes unity for observations $T \geq 2008$, otherwise zero.

Screening procedure The following screening procedure has been applied to the data to avoid excessive outliers or further implausible values.

- Drop observations with negative values for the following variables: w, lev, $lglev$, $liquidity$, $collat$ and $dyndebtshare$.
- Drop observations for which $w \leq 0$.
- Drop observations of the 5% and 95% percentiles of the following variable: ik, $intcf$, $solvency$, $liquidity$, $lglev$, lev, $collat$, $dyndebtshare$, $factor1$ and $factor2$.
- Drop observations of the 97.5% percentiles of the following variable: w, roi.
- Drop observations of the 95% percentiles of the following variable: cf, d.
- Drop observations of the 2.5% and 97.5% percentiles of the following variable: gt.

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Appendix: Tables

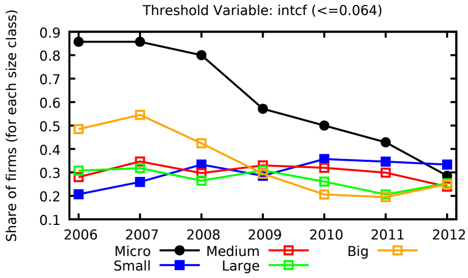
Component	**Eigenvalue**	**Proportion**	**Cumulative**
1	2.952	0.422	0.422
2	1.327	0.190	0.611
3	0.961	0.137	0.749
4	0.745	0.107	0.855
5	0.531	0.076	0.931
6	0.318	0.045	0.976
7	0.166	0.024	1.000

Component loading	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**
lev	0.472	0.230	-0.412	0.130	-0.149	-0.007	0.718
lglev	0.404	0.419	-0.466	0.018	0.055	0.086	-0.658
intcf	0.405	-0.255	0.276	-0.041	-0.809	-0.060	-0.187
collat	-0.029	0.588	0.508	0.620	-0.051	-0.093	-0.002
solvency	-0.470	0.121	-0.245	0.136	-0.423	0.711	0.024
liquidity	-0.185	0.587	0.142	-0.723	-0.205	-0.161	0.102
dyndebtshare	0.440	0.019	0.446	-0.236	0.312	0.670	0.074

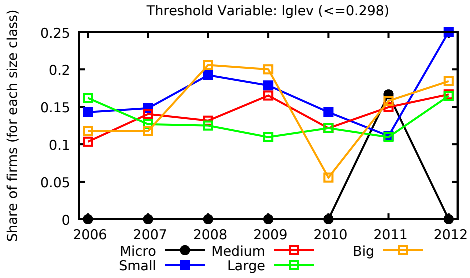
NOTE: Eigenanalysis of the correlation matrix. The variables *lev*, *lglev*, *intcf*, *collat*, *solvency*, *liquidity* and *dyndebtshare* refer to leverage, long-term leverage, interest-coverage ratio, collateral, solvency, liquidity and the dynamic debt share.

Table 7: Principal components analysis. Sample: 2006–2012.

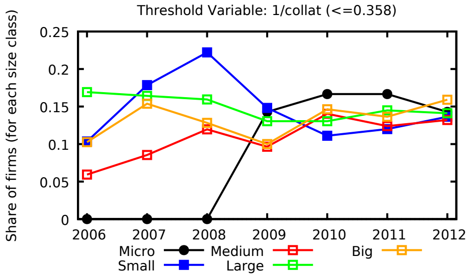
Appendix: Figures



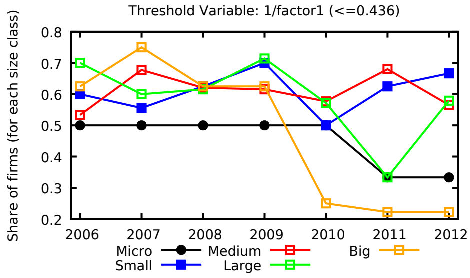
(a) Interest coverage ratio: *intcf*



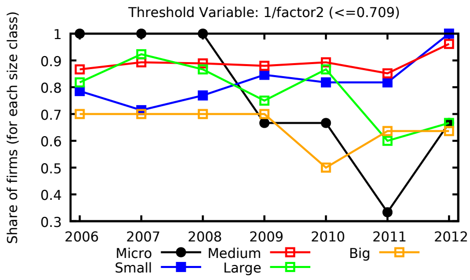
(b) Total long-term liability to total equity ratio: *lglev*



(c) Inverse of collateral: $1/collat$



(d) Inverse of the 1st common factor: $1/factor1$



(e) Inverse of the 2nd common factor: $1/factor2$

Figure 4: Share of firms (for each size class separately) falling below an estimated threshold over time. Sample: 2006–2012.