

THE ROLE OF INTERDEPENDENCIES
BETWEEN THE MICRO AND MACRO LEVEL
IN EXPLAINING INVESTMENT DYNAMICS
AND ITS DETERMINANTS

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This doctoral thesis consists of the following three papers:

1. Jan-Christopher Scherer (2019):
Firm-Level Data and the Dynamics of Aggregate Investment: A Structural Factor-Augmented Autoregressive (SFAVAR) Approach (unpublished)
2. Oliver Holtemöller and Jan-Christopher Scherer (2018):
Sovereign Stress, Banking Stress, and the Monetary Transmission Mechanism in the Euro Area
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3. Jan-Christopher Scherer (2020):
Heterogeneous Investment Dynamics in the Euro Area and the Interaction Between the Micro and the Macro Level in a Firm-Level Panel Analysis (unpublished)

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Overview

„Aggregate investment is an important topic. Countries and firms are often judged by their performance along this dimension, since investment is viewed as providing hope for future prosperity.“

Ricardo J. Caballero, 1997

Investment is a key component for the dynamics and development of economic conditions in various dimensions. In the short-run, it is a major driver of fluctuations in the business cycle, as it is pro-cyclical and usually the most volatile component of GDP. In the long-run, investment in new capital and technologies substantially determines the production possibilities and thus the growth of firms and economies. On the microeconomic level, investment is an important margin of adjustment for the firm optimizing its profit. And on the aggregate level, macroeconomic output and development are influenced by the collective individual investment decisions of firms. Importantly, the different dimensions interact with each other. Short-run fluctuations in the business cycle influence long-run growth and long-run growth expectations in turn influence short-run fluctuations. At the same time, firms take into account the macroeconomic environment under which they are operating while simultaneously and continuously forming this environment through their actions.

In this doctoral dissertation I empirically examine the interactions between microeconomic and macroeconomic investment to address the central research question behind all three chapters: How are investment and its determinants on one level affected by and in turn

affect the respective other level. Two different large firm-level data sets with balance sheet information of German and Euro area firms, respectively, form the basis for the empirical analyses in this dissertation, allowing direct access to microeconomic investment and determinants thereof. The firm-level information is then combined with aggregate data to examine the interactions between the two levels and, based on the central research question, derive and examine specific aspects of this guiding theme. The first of these specific aspects, explored in chapter 1, is the question on how microeconomic information can be utilized in an aggregate analysis and how, and if so under which conditions, it can help in explaining the dynamics of aggregate investment. The second aspect, which is explored in chapter 2, is the question on how macroeconomic factors influence financing costs at the firm-level, a key determinant of investment. The last aspect of the underlying central research question, addressed in chapter 3, is the question on how interactions between aggregate and firm-level data affect firm-level investment. The chapter also examines whether these effects differ between Euro area countries and how the interaction can help explain observed differences in aggregate investment across countries.

This doctoral dissertation therefore comprehensively researches the different aspects of the interaction between microeconomic and macroeconomic investment and its determinants, micro to macro as well as macro to micro. While the specific research questions and analyses differ in their approach and conclusions, the overall empirical result derived from this dissertation is unambiguous: Interactions between the aggregate and the firm-level play an important role in shaping the dynamics of both macroeconomic and microeconomic investment and a thorough understanding and recognition of these effects will enhance our understanding of the complicated and fascinating subject investment, irrespective of the level in question.

This introduction provides a frame of reference, in which I briefly recapitulate the most important developments in the research on investment. In line with the focus of this dissertation, I concentrate on the issue of investment in fixed capital in the overview. While a short overview cannot do justice to the complexity and multiplicity of a century of research on investment, I outline the most important steps and strands. Starting with the literature on

microeconomic investment, I first examine how investment decisions of individual firms have been explained and modeled. Second, I illustrate how the research on aggregate investment and its dynamics has evolved over time. With these two strands of literature as foundation of our understanding of investment, I then turn to the aspect at the core of this doctoral dissertation, the interdependencies and interactions between microeconomic and aggregate investment, providing the starting point for the empirical analyses in the following chapters.

Firm-level investment

One of the first considerations on how investment is determined was developed with the accelerator model of Clark (1917), based on the observation that investment is highly correlated with output growth. In this model, capital of a firm was assumed to be a fixed proportion of output. Investment then follows as the changes in capital over time. Focusing entirely on quantity variables and not regarding price variables, the simple accelerator model and its extensions (see, for example Clark (1944)) performed well empirically.

A different approach was the work of Fisher (1930), who postulated that investment should rather be affected by price variables, specifically the user cost of capital. However, while based on marginal conditions and thus superior to the accelerator model in theory, the model performed less successfully empirically.

An additional concept to explain investment on the firm-level can be found in Keynes (1936). In his *General Theory* investment demand depends on the marginal efficiency of capital, defined as the prospective yield of an asset compared to its replacement cost.

A more formal approach to investment demand in line of Fisher (1930), but based on firms' optimization behavior was then developed by Chenery (1952), Jorgenson (1963), Jorgenson (1967), Hall & Jorgenson (1967) and Eisner & Nadiri (1968), among others, with the neoclassical model.¹ In this framework, firms choose their capital stocks to maximize the discounted flow of profits over an infinite horizon. The optimal capital stock can be obtained in every period and depends on the level of output and the user cost of capital, which in turn is de-

¹ See also Jorgenson (1971) for an early survey on this class of models.

terminated by the price of new capital, the interest rate, the depreciation rate and taxes. The necessary changes in the actual capital stock to achieve the optimal one constitute optimal investment in each period.

Among the most criticized assumptions of the neoclassical model were its disregard of the endogeneity in choosing the optimal capital stock conditional on output, the assumed distributed lags for the implementation of new capital and the treatment of expectations as being not forward-looking.² To address these issues, researchers began modeling dynamics directly in the optimization problem of the firm by introducing adjustment costs of investment. These adjustment costs are a convex function of investment. Therefore, the optimization problem of the firm becomes dynamic, as it has to plan the path of future investment to maximize profits. The resulting optimality condition equates the expected marginal benefits of investing – measured by the shadow price of capital – to its marginal costs. Accordingly, investment depends on the ratio of these two variables, called marginal q . While the shadow price of capital and thus marginal q are unobservable, Brainard & Tobin (1968), Tobin (1969) and Tobin (1978) in their q theory of investment proposed utilizing stock market information, namely the ratio of a firm’s financial value to the replacement cost of its capital stock.³ This ratio, called average q , is observable. Hayashi (1982) and Hayashi (1985) showed that under certain conditions average q equals marginal q and Abel (1979) demonstrated that the q model follows from the neoclassical model with convex adjustment costs. In the q theory a firm will invest if the value of average q is larger than 1, as in this case the expected marginal benefits of investing will be larger than its marginal costs. In theory, by using stock market information, q captures all relevant future conditions affecting investment decisions in one observable variable.

While theoretically elegant, the q model’s unsatisfactory empirical performance prompted researchers to revisit the imposed assumptions. One direction of research focused on the assumption of convex adjustment costs. Rothschild (1971) derived the implications of different forms of adjustment costs for investment and concluded that the arguments in favor of

² See, for example, Chirinko (1993) for an in-depth analysis of the criticism on neoclassical models.

³ This takes up the considerations in Keynes (1936) cited above, who thought investment to depend on the ratio of the market value of capital to its replacement cost.

convex adjustment costs are not convincing. Similarly, Abel & Blanchard (1986) argue that the q model based on the standard assumptions, including convex adjustment costs, does not match the empirical evidence.

As a consequence, several causes for non-convex adjustment costs have been explored. One important aspect is the concept of irreversibility and uncertainty of investment. If the costs of an investment cannot fully be recovered in later periods by selling the asset in question, then investing entails a fixed cost component. Therefore, under irreversibility firms have to incorporate expectations about future conditions when making investment decisions (Arrow 1968, Nickell 1974). Since future price developments and returns are uncertain, there is a value of the option of waiting and postponing investment today (see, for example, Dixit, Dixit & Pindyck (1994)).

Combining irreversibility and adjustment costs with a fixed component in a more general q -model framework, Abel & Eberly (1994) show that optimal investment behavior of the firm comprises three regimes with positive, zero and negative gross investment, respectively, given q . Therefore, with these investment frictions, the response of investment is not linear, but rather a non-decreasing function of q .

With larger firm-level data sets becoming available, panel data models allowed to empirically test the implications of theoretical work and thus deeper insights into the investment behavior of firms and the nature of adjustment costs. With strictly convex adjustment costs, firms will spread out investment over several periods in order to minimize the associated costs. Given a certain divisibility of investment projects, this implies that firms' investment will be smooth over time, with positive investment in every period and no dramatic changes in the size of investments undertaken. Examining manufacturing plant data, Doms & Dunne (1998), however, show that investment is lumpy, i.e. occurs in infrequent spikes of increased activity that account for a substantial part of total investment of the firm over the sample period. They find that the observed investment patterns can be explained best by (S, s) type models, in which firms compare the actual with their desired capital stock and only invest (disinvest) if the difference exceeds the threshold S (s). Below these thresholds changing the capital stock is not optimal, thus creating a range of inactivity (besides small replacement

and maintenance investment). In a similar line Barnett & Sakellaris (1998) test the results of Abel & Eberly (1994) and confirm the nonlinear relationship between investment and q . In addition, Cooper, Haltiwanger & Power (1999) find that the probability of a plant to undertake such a large investment is increasing in the time since the last activity, i.e. investment episodes exhibit negative serial correlation.

More generally testing the form of adjustment costs, Caballero, Engel, Haltiwanger, Woodford & Hall (1995) find evidence of nonlinearities in the investment behavior of plants, with plants reacting asymmetrically to excesses or shortages of capital and the size of these shortages. They conclude that nonconvexities in adjustment costs are consistent with the data. In the same line, Cooper & Haltiwanger (2006) test a structural model of adjustment and find that a specification with non-convex adjustment costs and irreversibility provides the best fit of their plant-level data.

In standard (S, s) models, the thresholds triggering capital adjustments are deterministic. This strong assumption, however, can be relaxed. Caballero (1999) assume the adjustment cost function to be an i.i.d. random variable. This results in a probabilistic adjustment rule in which there is a higher probability of adjustment for larger capital imbalances while at the same time allowing these adjustments to differ across firms and over time.

Another strand of literature focused on the effects of financial frictions on investment. Although Modigliani & Miller (1958) found that – under certain conditions – the financial characteristics of a firm leave its capital market value unaffected and thus do not matter for its investment decisions, empirical studies like Fazzari, Hubbard & Petersen (1988), Hubbard, Kashyap, Whited et al. (1995) or Gilchrist & Himmelberg (1995) illustrate that financing constraints do affect the investment of firms even when conditioning on q and that firms' liquidity and especially cash flow are important determinants of investment. Likewise, Cleary (1999) finds a high sensitivity of investment decisions with respect to liquidity. In addition, Almeida & Campello (2007) examine the impact of firms' asset tangibility on their sensitivity of investment to cash flow and find a positive effect for financially constrained firms. Moreover, Campello, Graham & Harvey (2010) find that financially constrained firms plan to reduce investment stronger than unconstrained ones. The results of other studies

like Gomes (2001), however, indicate that cash flow only matters in explaining investment if q is disregarded. Furthermore, there is also disagreement about the relationship between the sensitivity of investment to cash flow and financial constraints, with some studies finding a positive relationship (for example, Fazzari et al. (1988), Almeida & Campello (2007) and Mulier, Schoors & Merlevede (2016)) and others finding the opposite (for example, Kaplan & Zingales (1997) and Cleary (1999)).

Building on the work of Dixit et al. (1994), researchers have reexamined the effects of uncertainty on corporate investment. Bloom, Bond & Van Reenen (2007) use share price volatility to construct a measure of uncertainty at the firm level. They find that in their model with partial irreversibility higher uncertainty reduces the short-run adjustment of investment to demand shocks. Similarly, Gulen & Ion (2016) find a negative effect of the aggregate level of uncertainty with respect to future policy and regulatory outcomes on firm investment and that the effect is stronger for firms with a higher degree of irreversibility.

Aggregate investment

The literature on aggregate investment usually either utilizes classic investment equations with aggregate data or models aggregate investment in frameworks designed for the study of macroeconomic dynamics and business cycles as a whole. The commonality of both approaches lies in the disregard of the heterogeneity of economic agents, either by using aggregate data or by assuming representative agents in the microfoundation of the models. Much of the early research on aggregate investment resulted from and evolved conjointly with the work on firm-level investment, as these theories were based on fundamental economic principles without specification and thus more general applicability to both the micro and the macro level. As such, the neoclassical model was used with aggregate data to explain the behavior of aggregate investment (see, for example, Hall & Jorgenson (1967)). Similarly, the q model of investment can be used to analyze aggregate investment, given an aggregate measure of q (see, for example, Schiantarelli & Georgoutsos (1990)). Accordingly, the early approaches

to aggregate investment relied on the same theories and partial-equilibrium models developed for the analysis of firm-level investment, just applied with macroeconomic data.

However, another direction of research focused on explaining aggregate dynamics more generally, building on Keynesian macroeconomic theory (Keynes (1936)). The IS-LM framework (Hicks (1937) and Hansen (1953)) provides a framework to jointly analyze the interest rate and gross domestic output (GDP) and the AS-AD model developed later incorporated the labor market and was used to study the interaction between GDP and the aggregate price level. In both models, aggregate investment is modeled as a function of GDP and the interest rate.

While used extensively, many aspects and underlying assumptions of the models based on Keynesian macroeconomics have been heavily criticized, especially the lack of microfoundations and expectations.⁴ The importance of the latter has been stressed by Lucas (1976) in his famous Lucas Critique.

In light of the critique, a new dynamic stochastic general-equilibrium (DSGE) framework for aggregate dynamics was developed with the real business cycle (RBC) model, starting with the work of Kydland & Prescott (1982) and Long & Plosser (1983) and extended by King, Plosser & Rebelo (1988). In this model with microfoundations and rational expectations, business cycle fluctuations are driven by technology shocks and the representative firm maximizes profits by choosing capital such that the marginal product of capital equals the rental rate of capital.

While the RBC model is able to match the time series properties of key macroeconomic variables over the business cycle, it does not match the fluctuations in employment observed in real economies. Moreover, central assumptions of the model have been criticized. Most importantly, RBC models require unrealistically large technology shocks and imply technological regress to explain recessions, they assume prices and wages to adjust immediately, markets to be perfectly competitive and they have no role for monetary policy (see, for example, the overviews in King & Rebelo (1999) and Rebelo (2005)).

⁴ See, in addition, Colander (1995) and Romer (2000) for a systematic analysis of the models' shortcomings.

Addressing these issues, researchers incorporated market imperfections in the form of sticky prices and wages, modeled firms as monopolistically competitive and allowed for a more complex system of shocks to affect the dynamics of the model. In this framework, known as New Keynesian DSGE model, monetary policy does affect the real economy in the short-run. Starting with the seminal papers by Clarida, Gali & Gertler (1999), Smets & Wouters (2003), Christiano, Eichenbaum & Evans (2005) and Smets & Wouters (2007), New Keynesian DSGE models have become the standard model of modern macroeconomic research and remain so until this day. While the New Keynesian DSGE model is a general-equilibrium model and as such analyzes the macroeconomic dynamics of an economy as a whole, aggregate investment is modeled specifically. Based on the investment Euler equation from household optimization, Smets & Wouters (2007) derive an investment function of the representative firm which depends on past and expected future investment, an investment-specific technology shock and the real value of the existing capital stock.

Interaction between micro and macro level

Against the background of the cited models and theories, I now turn to the interactions between firm-level and aggregate investment.

In the (S, s) models described above, firms are heterogeneous in the sense that on the firm-level there is a distribution of firm capital gaps and investment. As a consequence, the dynamics of the resulting aggregate investment depends on the timing and the synchronization of firm-level actions and cannot be captured by a representative firm. The importance of the microeconomic distribution for aggregate dynamics is demonstrated by Doms & Dunne (1998) who establish that there is a significant correlation between fluctuations in aggregate investment and the incidence of plants having large investment episodes. Similarly, Gourio & Kashyap (2007) show that the number of firms undergoing such large investment episodes explains most of the variation in aggregate investment.

Several papers have studied the effects of lumpy firm-level investment on aggregate dynamics. Bertola & Caballero (1994) examine the implications of a microeconomic model of

irreversibility for aggregate investment. Due to the heterogeneity of firms with respect to investment spending, caused by idiosyncratic uncertainty, aggregating firm-level investment requires information on the cross-sectional distribution, as the dynamics of the mean of this distribution – and thus aggregate investment – depend on the moments of the distribution. They conclude that the resulting aggregate investment series from their procedure matches U.S. data. Caballero (1999) introduce a more general (S, s) model with firms facing random fixed costs of adjusting the capital stock. As a consequence, the capital adjustment rule takes the form of an increasing adjustment hazard function, i.e. a probability of adjusting instead of deterministic thresholds. They find that this non-linear generalized (S, s) model performs better in explaining aggregate investment than models with quadratic adjustment costs because it allows for the number of firms to change over the business cycle. Therefore, how strongly aggregate investment reacts to aggregate shocks will vary over the business cycle as well. This change in the marginal response of aggregate investment to shocks is also found in Caballero et al. (1995) and has important implications for the dynamics of aggregate investment, as a higher synchronization in the underlying distribution of firms can amplify the effects of aggregate shocks on the economy.

While the literature has reached a consensus about the lumpy nature of microeconomic investment, the views on the consequences of this characteristic for aggregate dynamics, however, are not unanimous. As described above, the literature on (S, s) -type models concludes that microeconomic lumpiness plays an important role for aggregate investment. The reasoning in this framework, however, is based on exogenous shocks and thus abstracts from effects of general equilibrium.⁵ This view has been challenged by subsequent results based on DSGE models. Veracierto (2002) examines irreversible establishment-level investment in a RBC model and find them to not be important for aggregate investment dynamics. Similarly, Thomas (2002) incorporates a generalized (S, s) model in a RBC model and finds, when considering productivity shocks, the response of the modified model to not be different from results implied by standard RBC models, concluding that lumpy microeconomic invest-

⁵ Caballero (1999) in his overview states that general equilibrium effects smooth the response of aggregate investment to shocks and should be of great importance.

ment is not important for aggregate investment dynamics because of the effects of relative price changes. The same result was found by Khan & Thomas (2008) in an extended model framework. However, examining the effects of lumpy investment in a New Keynesian DSGE model, Sveen & Weinke (2007) show that lumpiness does matter for aggregate investment dynamics and relate this to imperfect competition in goods markets and/or sticky prices as the reason why. Since these mechanisms are absent from standard RBC models, they were not found using the corresponding framework. This view is further strengthened by the results in Gourio & Kashyap (2007) who using plant-level data find that the extensive margin, i.e. the number of firms undergoing large investment episodes, explains most of the variation in aggregate investment. Based on this result they modify the model of Thomas (2002) such that the extensive margin plays a more prominent role and the empirical data is more accurately captured. With these changes they confirm the importance of lumpiness for aggregate investment and conclude that the previous findings of no relevance are not due to general equilibrium effects per se, but rather depend on the calibration of the model in question. This seems to constitute a reasonable conclusion for the question at hand.

Another concept of how the distribution of firm-level investment can affect the dynamics of aggregate investment is proposed by Gabaix (2011). His concept of granularity is built on the empirically established fact that the distribution of firm sizes is fat-tailed and can be modeled by a power-law distribution. This implies that the number of large firms is higher than what would be expected under a Normal distribution. Gabaix then shows that under a power-law distribution idiosyncratic firm shocks do not balance out on the aggregate level, but affect aggregate dynamics. His results indicate that idiosyncratic shocks to the 100 largest firms in the US explain about one-third of output growth volatility. Accordingly, not only aggregate shocks influence the business cycle, but also microeconomic shocks to large firms which do not cancel out in aggregation, but are passed through. Similarly, Acemoglu, Carvalho, Ozdaglar & Tahbaz-Salehi (2012) argue that input-output linkages across sectors can propagate idiosyncratic shocks such that aggregate fluctuations arise. Moreover, Amiti & Weinstein (2018) identify idiosyncratic bank loan supply shocks and find them to be an

important determinant of aggregate investment. Clearly, idiosyncratic shocks matter for the aggregate.

Simultaneously, aggregate investment and the general macroeconomic conditions heavily influence firm-level investment. When deciding about the profitability, timing, size or the financing of new investment, the firm has to take into account the demand for its products or services and the factors of its production. Accordingly, any developments on the aggregate level and aggregate shocks affecting demand or supply will interact with and influence firm-level investment.

Besides these general influences associated with business cycle fluctuations and changes in the macroeconomic environment, aggregate investment also affects firm-level investment by determining the long-run production possibilities of a country or economic area. Firms' collective investment in research and development will over time generate new technologies and improve aggregate productivity, which in turn will benefit the individual firm and thus influence its investment decisions.

Chapter overview and contribution of this dissertation

The following three chapters form the core of this dissertation and examine empirically the effects of interdependencies between the micro and macro level on investment and its determinants.

Chapter 1, *Firm-level Data and the Dynamics of Aggregate Investment: A Structural Factor-Augmented Vector Autoregressive (SFAVAR) Approach*, analyzes empirically how microeconomic information affects the dynamics of aggregate investment. Using a panel data set I first confirm the lumpiness of microeconomic investment for German firms in the spirit of Doms & Dunne (1998). Then two different mechanisms are explored to examine the dynamics of aggregate firm investment. First, I address the question of how firm-level information can be incorporated into macroeconomic analysis. To this end, I estimate factor models on different determinants of firms' financing conditions, thereby capturing the main directions of variation in the sub-sets of the underlying firm-level data and providing a readily

available aggregate measure of this information. The resulting factors are then included in standard macro-level structural VAR models to yield factor-augmented SVAR models. The results indicate that the financing conditions on the firm-level, while controlling for aggregate dynamics and the level of interest, have a significant impact on aggregate firm investment and help explain its variation. However, this result only holds in times of financial distress. Excluding the Great Recession of 08/09, the factors are not found to provide additional explanatory information for aggregate investment, indicating a conditional importance of firm-level information. Second, I examine effects of granularity as introduced by Gabaix (2011). Shocks on the micro-level alter the distribution of firm-level investment which, based on the concept of granularity, should have aggregate effects as well. Computing the moments of the underlying distribution of firm-level investment allows to assess the changes in the distribution over time and to test the aggregate implications thereof. Based on a SVAR framework I do not find significant effects of these distributional changes. Finally, I address a common issue encountered in applied macroeconomic research by assessing the effects of interpolation of lower frequency data. While the aggregate variables in the S(FA)VAR are at a quarterly frequency, the firm-level data is based on annual balance sheet information. Extracting factors from this data yields annual variables as well, which are interpolated to quarterly frequency to match the remaining macroeconomic variables. I examine the implications of this transformation in a Monte-Carlo simulation and find that interpolating the annual data does not bias the results.

In chapter 2, *Sovereign Stress, Banking Stress, and the Monetary Transmission Mechanism in the Euro Area*, which is joint work with my supervisor Oliver Holtemöller, the focus is on financing costs as an important determinant of firm-level investment and how these are influenced by macroeconomic conditions. We examine how sovereign stress and banking stress have affected firms' financing costs in the Euro area during the European debt crisis. Starting from the observation that aggregate bank lending rates for stressed (Ireland, Italy, Spain and Portugal) and non-stressed (Austria, Finland, France and Germany) Euro area countries, after evolving with similar dynamics, started to diverge in 2011, we show that

corporate financing costs in stressed countries and in non-stressed countries in the Euro area moved in significantly different directions during the years 2011 and 2012, even after controlling for firm-specific characteristics, while they moved in the same direction before the sovereign debt crisis. The results of our firm-level panel model indicate that sovereign stress and banking stress significantly increased corporate financing costs and thus help explain the observed differences between stressed and non-stressed countries. Moreover, the two macroeconomic stress factors also impaired the monetary transmission mechanism. Since the level of banking stress in stressed countries remained elevated, this suggests that while the European Central Bank's asset purchase programs helped to reduce the financing conditions of firms during and in the aftermath of the sovereign debt crisis, the transmission mechanism was still impaired. Considering theoretical models, the qualitative results in this chapter are to be expected. But, to the best of our knowledge, we are the first to quantify these effects on corporate financing costs as well as the monetary transmission mechanism. The chapter therefore highlights the importance of aggregate economic conditions for the financing costs of individual firms, which in turn is an important determinant of investment.

In the last chapter, *Heterogeneous Investment Dynamics in the Euro Area and the Interaction Between the Micro and the Macro Level in a Firm-Level Panel Analysis*, I examine the interactions between the aggregate and the firm-level to assess how firm-level investment is affected by macroeconomic conditions. As a first step I establish differences in the evolution of aggregate investment across Euro area countries in the Great Recession and its aftermath. To this end, I specify an error correction panel model based on the theoretical investment function of Smets & Wouters (2007). Estimating this model using a Pooled Mean Group (PMG) estimator, I find significantly different long-run equilibria across the two subgroups of stressed (Italy, Spain and Portugal) and non-stressed Euro area countries (Austria, Finland, France and Germany). To examine the reasons for these differences, I then turn to firm-level investment data. Building on a (S, s) type model of investment as in Caballero (1999), I motivate an interaction effect between firm-level determinants of investment, specifically cash flow, and GDP growth to explain differences in the evolution of aggregate investment across

different Euro area countries. The characteristics of (S, s) type models are implemented empirically by specifying a dynamic error correction panel model. Using a large data set on firms' balance sheet information together with country-level data in this framework, I can test the proposed interaction effect. The results show that the effect of cash flow on firm investment does positively depend on GDP growth. However, this interaction is only confirmed for firms in stressed countries, but not for the ones in non-stressed Euro area countries. I conclude that, since in the Great Recession and its aftermath GDP growth was lower in these stressed countries, the estimated interaction effect created a negative feedback effect. This mechanism accelerated the prolonged economic downturn and can help explain the observed differences in the evolution of aggregate investment between stressed and non-stressed countries.

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Chapter 1

Firm-Level Data and the Dynamics of Aggregate Investment: A Structural Factor-Augmented Vector Autoregressive (SFAVAR) Approach

Abstract

In this paper I study the interactions between the micro and macro level by assessing the effects of micro-level information on the dynamics of aggregate investment. Utilizing a large data set of German firms spanning the years 1991–2011, I estimate factor models for variables commonly used to explain firm-level investment and include the resulting factors as well as moments of the micro-level investment distribution in structural macroeconomic FAVAR analyses. I find that firm-level information does not help in explaining the dynamics of aggregate investment in normal times, but does so when including the Great Recession, highlighting the conditional importance of firm-level variables. Shocks to the moments of the micro-level investment distribution, however, do not help explain aggregate investment.

1.1 Introduction

The literature has long examined the determinants of aggregate investment, but its volatility has not been completely explained yet. However, as aggregate investment is of great importance for the fluctuations of the business cycle, a better understanding of the dynamics of this component would enhance our understanding of macroeconomic fluctuations in general. Not only does investment matter quantitatively – aggregate fixed investment accounted for about 20.7% of German GDP in 2018 – but it is also typically the most sensitive component of output, responding strongly to shocks and thus marking turning points in the macroeconomic environment. Looking at the Great Recession and its aftermath, we see, for example, that aggregate fixed investment led the recession with a contribution of -1.9 percentage points to the growth of overall GDP in 2009, but even more strongly added to the following expansion with growth contributions of 1.0 and 1.4 percentage points in 2010 and 2011, respectively.

Figure 1.1 displays the cyclical components of German gross domestic product, private consumption, productivity and aggregate firm investment¹ over the period 1991–2011, generated by applying the Hodrick-Prescott filter to the respective time series. In addition, table 1.1 depicts the standard deviations as well as the correlations of the cyclical components of the four variables with GDP to quantify the graphical impressions. As can be seen, firm investment is procyclical and much more volatile than GDP and private consumption. Understanding the dynamic evolution of aggregate investment therefore is crucial for a more complete understanding of the business cycle.

In this paper I examine two mechanisms through which microeconomic information affects the dynamics of aggregate investment – the influence of microeconomic variables related to the financing abilities of a firm which are important for firm-level investment decisions and the effects of granularity (i.e. the pass-through of micro-level shocks to the aggregate) as captured by the moments of the underlying investment distribution – to see whether micro-level data helps to better explain the dynamics of aggregate firm investment as compared to

¹ See section 1.6 in the appendix for the exact definition of this variable.

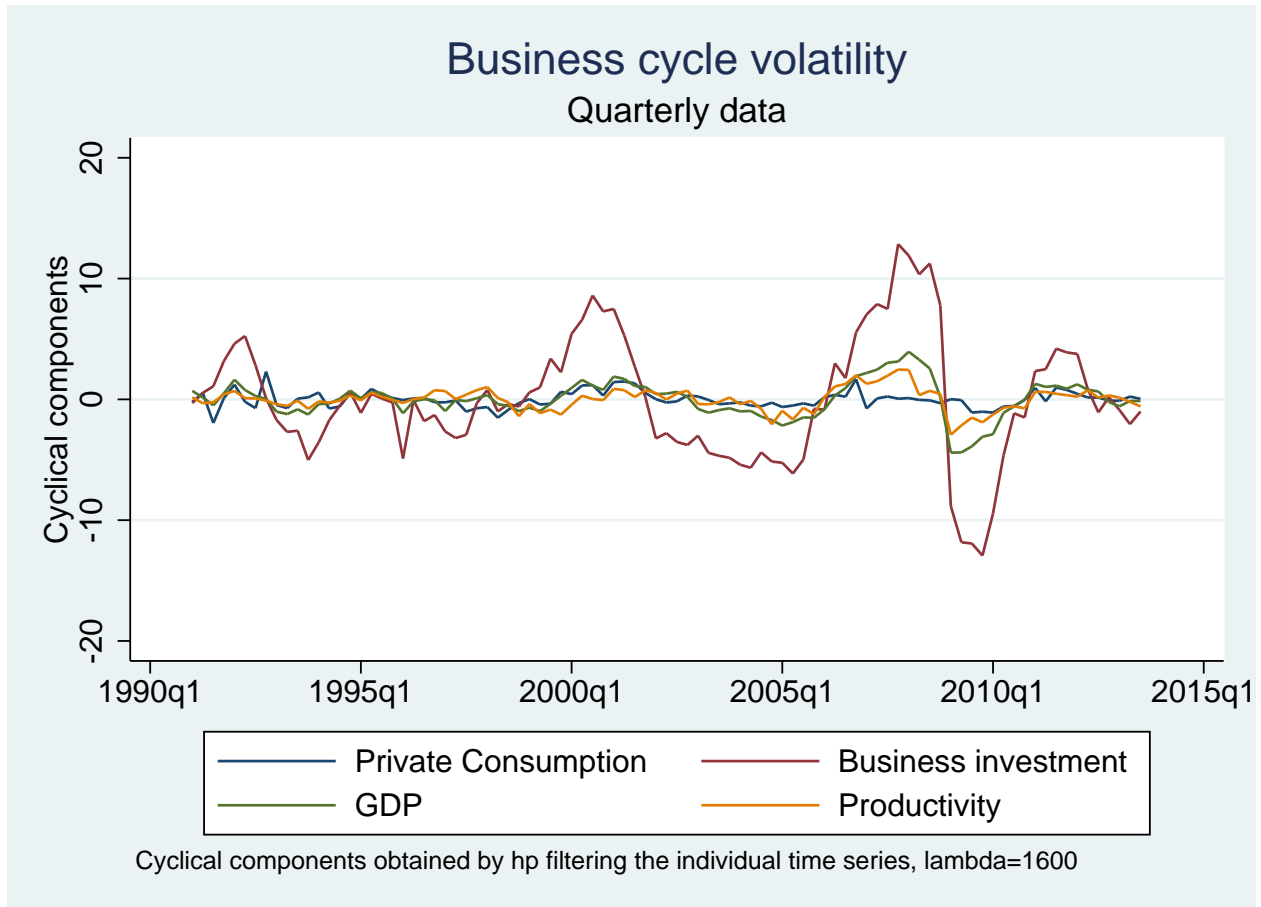


Figure 1.1: Excess volatility of business investment

Notes: Depicted are the cyclical components of private consumption, business investment, GDP and labour productivity for Germany, obtained by applying the Hodrick-Prescott filter to the respective time series over the sample 1991–2011. Data source: German Statistical Office (Destatis) and own calculations.

a purely macroeconomic approach. The first analysis captures the information contained in the microeconomic variables in factor models, thus focusing on the weighted means of the underlying firm-level investment determinants, whereas the second analysis concentrates on the effects of the higher moments of the firm-level investment distribution itself. I find that financing variables on the micro level do indeed have a significant impact on aggregate firm investment, however, this effect only seems to matter in times of financial distress. In normal times the firm-level information does not help explain aggregate firm investment. Moreover, I find the effects of granularity to be negligible for aggregate dynamics.

Table 1.1: Business cycle statistics

Variable	Standard deviation	Correlation with GDP
GDP	1.50	1.00
Consumption	0.69	0.45
Investment	5.09	0.89
Productivity	0.93	0.85

Notes: Statistics are calculated for the cyclical components of private consumption, business investment, GDP and labour productivity for Germany, obtained by applying the Hodrick-Prescott filter to the respective time series over the sample 1991–2011. Data source: German Statistical Office (Destatis) and own calculations.

While important for the dynamics of macroeconomic variables, investment decisions are made at the microeconomic level by intertemporally optimizing firms. Ultimately, these microeconomic decisions taken together constitute aggregate investment and are the source of macroeconomic fluctuations and volatility in this variable. In order to understand these aggregate dynamics, we therefore have to understand firm-level dynamics and the determinants of firm-level investment decisions.

From the empirical analyses of micro-level investment data as in Doms & Dunne (1998) and Gourio & Kashyap (2007) we know that micro-level investment is lumpy, meaning it does not occur smoothly and rather uniformly in every period, but in infrequent investment spikes with episodes of very low investment spending in between them. Gourio & Kashyap (2007) also showed that these spikes are quantitatively important, as they contain a large share of a firm’s total investment spending.

We also know that access to finance is one of the most important determinants of firm-level investment. Funding can be generated within the normal business activity of the firm through retained profits (internal financing) and obtained from sources outside of the firm, especially financial markets and banks (external financing). Firm fundamentals which measure the ability for internal financing are cash flow, as a gauge for the liquid assets circulating within the firm and naturally profit itself, as higher profit allows for higher retained funds that can subsequently be used for investment. The most important source for external financing in

Germany and especially for small and medium enterprises is credit obtained from banks. External funding is therefore reflected in firms taking on higher debt. In addition, I consider the price of this form of external funding by incorporating the financing costs of firms, measured as interest payments divided by total liabilities. In sum, I include four variables in my analysis to capture firms' access to finance: Cash flow and profitability as measures of internal financing and debt and financing costs as measure of external financing.

However, these measures are not readily available at the macro level to be incorporated in an analysis of aggregate dynamics. Accordingly, two important questions that arise are i) how to capture the information from the micro level and ii) how to include them in the analysis of aggregate investment dynamics. In this paper I propose to approach these questions by using a dynamic factor model (DFM) and a structural factor-augmented VAR (SFAVAR), respectively. In the DFM a set of latent factors f drives the comovement of n variables over time. Since typically f is much smaller than n , the model allows explaining a large proportion of the variance in the data by means of only a few factors. Accordingly, the information of a broad set of variables can be used without facing degrees-of-freedom problems. Specifically, by using the DFM I can summarize firm specific data on investment determinants into one factor. Augmenting a VAR model with these factors as additional variable then yields a factor-augmented VAR, which, via the extracted factors, can contain the information of more variables than otherwise possible in a standard VAR model (see, for example, Bernanke, Boivin & Eliasch (2005)).

As a second step in analyzing the effects of microeconomic characteristics on macroeconomic outcomes I examine the role of the firm-level investment distribution for the dynamics of aggregate investment.

Many microeconomic characteristics are washed out by aggregation and important information get lost all together. For example, the cross-sectional distribution of microeconomic investment can potentially change substantially between two periods. While these changes may contain valuable information (e.g. for extreme cross-sectional values in the tails of the distribution), due to the summation in the aggregation process they might not be reflected

in the aggregate time series, depending on whether and how different changes cancel each other out in the process.

The literature has examined this relation between microeconomic distributions and aggregate effects in the concept of granularity as introduced in Gabaix (2011). The starting point is the empirical observation that the distribution of many relevant economic variables follow a power law, in which the upper tail of the distribution is fat, i.e exhibits higher probabilities for extreme values and, corresponding to that, has higher third or fourth moments compared to a normal distribution. One important example for this type of relationship is the distribution of firm size, which has been found to follow a power law (see, for example, Axtell (2001) and Luttmer (2007) for the US, Gaffeo, Gallegati & Palestrini (2003) for G7 countries or Di Giovanni, Levchenko & Ranciere (2011) for France). Accordingly, there is some concentration of large firms in the economy, which has profound implications for the distribution of firm-level investment: Because the size of firms is positively correlated with their capital stock, the investment spending of these large firms is, at least in absolute values, large as well. In this vein, idiosyncratic shocks to firms can have aggregate effects, because with the fat-tailed distribution of firm sizes the mass of large firms with large investments in response to those shocks is high. Therefore, idiosyncratic shocks may not completely counterbalance each other. In his seminal paper, Gabaix (2011) for example finds that this granularity explains about one-third of GDP fluctuations in the US.

Because the granular effects of idiosyncratic micro-level shocks on aggregate fluctuations depend on the degree of fat-tailedness in the right tail of the underlying distribution (the large firms) and this fat-tailedness in turn can be assessed by its skewness, it follows that changes in the third moment reflect changes in the granularity of the underlying distribution. Accordingly, the mechanism outlined above predicts a higher pass-through of micro-level shocks to the aggregate when skewness and thus granularity is higher. Not underestimating the fat tails of the micro-level distribution is important, as episodes in which the skewness of the micro-level investment distribution is high imply a higher sensitivity of aggregate outcomes to firm-level shocks. Using firm-level investment data, I test this channel by constructing the time-series of cross-sectional moments in every year and examining the effects of shocks

to this moments on aggregate variables in my VAR analysis. This complements the factor analysis described above, as the factors by construction can not capture the characteristics of an underlying micro-level distribution, but represent weighted means. Combining both analyses, weighted means of investment determinants and moments of the micro-level investment distribution itself, therefore yields a more complete picture for the analysis of the dynamics of aggregate investment.

Employing a data set on firm-level balance sheets in combination with the FAVAR methodology thus allows a more complete analysis of aggregate investment dynamics by incorporating both microeconomic financing variables that are not available at the macroeconomic level and information on the underlying microeconomic distribution of investment as captured by the higher moments.

The remainder of the paper is organized as follows. Section 3.3 introduces the Ustan balance sheet data set of the Deutsche Bundesbank and examines the cross-sectional distribution of microeconomic investment. The methodology of dynamic factor models and the factor-augmented VAR is briefly summarized in section 1.3. Section 1.4 then presents the identification of the SVAR and SFAVAR models to be estimated. Results are presented in section 1.5. Finally, section 1.6 concludes.

1.2 Microeconomic data

1.2.1 Ustan data set

For the microeconomic data I draw on the Ustan data set (UDS) of the Deutsche Bundesbank (Becker, Biewen, Schultz & Weisbecker 2020) which contains the yearly balance sheet data of a multiplicity of firms. Being responsible for the bill of exchange transactions with German firms in the times before ceding this authority to the European Central Bank, the Bundesbank required detailed information of the respective firms in order for them to participate in the refinancing operations. After the third stage of the Economic and Monetary Union and the loss of this authority, the Bundesbank supplemented the existing but de-

cluding firm observations from the refinancing operations with additional balance sheet data from i) other financial firms working with these data and ii) non-financial firms who provide their own balance sheet data. In return for the information the Bundesbank offers a detailed analysis of the data, including a solvency assessment which can be used to facilitate external financing through for example private banks. As a result, a unique data set is available. Several features of the UDS suggest its use for the analysis at hand.

One of the most important features of this data is its high quality. Resting upon official balance sheet procedure, the data is compiled by the firms in accordance with legally binding German accounting standards and thus of very high quality. All legal requirements apply. Moreover, the data also feature a relatively long time dimension, as it is available from 1972 onwards. However, due to changes in the regulatory framework in 1986, there arguably is a structural break in the time series prohibiting the use of the entire time series for estimation. To account for this and to avoid noisy data problems due to the German reunification only the years 1991 to 2011 are included in the empirical specifications.

Besides these advantages, several issues of the UDS have to be taken care of. One major concern is the possibility of a survivor bias in the data, i.e. a positive selection and build-up of financially sound firms because of stricken firms becoming bankrupt and dropping out of the sample. However, an analysis in Bundesbank (1998) compares the probability of a bankruptcy within the UDS with general statistics of insolvency and concludes that a survivor bias in the data should be rather limited such that a broad range of different solvencies is represented in the sample. In addition, while interesting aspects of both the unbalanced and the balanced data set will be used in the descriptive part of this paper, the SFAVARs rely only on the balanced panel.

A more prevailing challenge to the validity of the data set is the unequal representation across sectors and legal forms. Since the basis of the data set is formed by the refinancing operations of the Bundesbank through trade bill transaction/promissory notes, strong coverage is predominantly given for those sectors in which this form of refinancing was traditionally

widespread.² With the broadening of the data base after 1999, the problem of insufficient representation of some sectors was considerably abated. These changes are analyzed explicitly in Bundesbank (2005).

Overall, with the combination of detailed, high-quality data of a large number of firms and the long time period covered, the UDS constitutes an almost ideal data set for the analysis at hand.

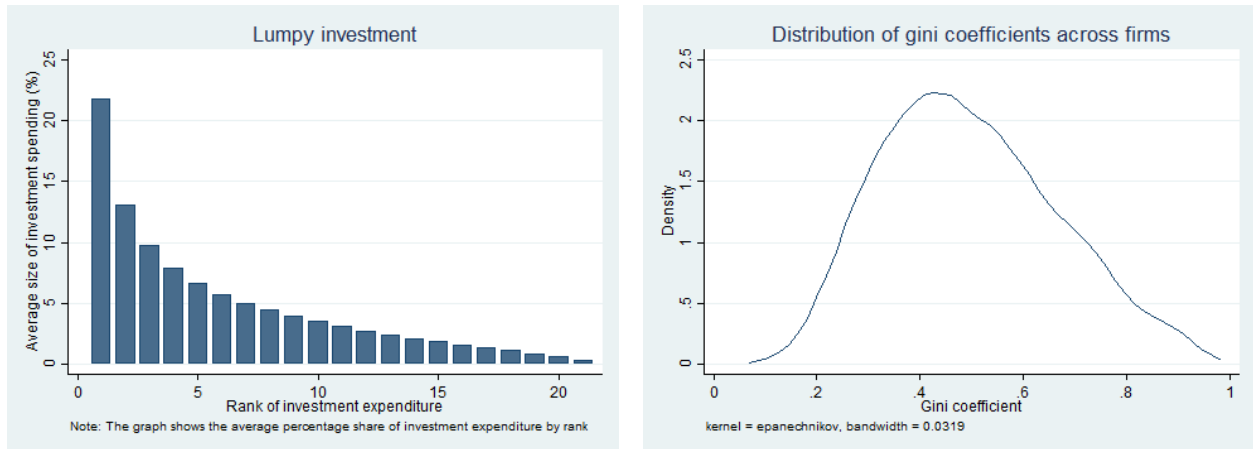
To gain deeper insights into the microeconomic data set this section concludes with an examination of the lumpiness of firm-level investment.

As described above, firm-specific investment spending is characterized by its lumpy nature: Firms' investment does not evolve smoothly over time but rather exhibits distinct alternations between periods of high investment spending and those of low activity. This fact is illustrated in figure 1.2a: The investment expenditures of every firm are ranked by size with rank 1 corresponding to the largest investment in the period between 1991 and 2011, rank two the second largest and so forth. From this the percentage shares of these ranks in the overall investment spending of the respective firm are computed, yielding 21 ranks and shares, respectively, for the 21 years spanning the data set. Cross-sectionally averaging these shares, I then compute the mean percentage share of every investment rank over all firms in the sample. Figure 1.2a reveals the lumpiness in the investment data, as the ordered investment shares decrease geometrically. Specifically, the first bar indicates that - on average - the largest investment spending of a firm between 1991 and 2011 accounted for 21.8% of its total investment that occurred in this 21 year period. The two largest shares combined represent approx. 35%, i.e. the two largest investment periods account for more than one third of overall investment spending.³

Another way of assessing the lumpiness inherent in the data is to compute for each firm the Gini coefficient of their respective investment spending over the 21 years in the sample, thereby quantifying the degree of inequality with respect to investment. Plotting the dis-

² For a detailed overview see table in Bundesbank (1998), p. 56.

³ The cited paper of Doms & Dunne (1998) finds similar values using US data on manufacturing plants over the period 1972-1988, with an average largest share of investment spending of 24.5% and 39.2% for the two largest shares combined.



(a) Investment shares

(b) Distribution of Gini coefficients

Figure 1.2: Lumpy investment

Notes: Panel a) depicts the mean of the percentage share of the n^{th} largest annual investment for all firms compared to their respective total investment, $n = 1, \dots, 21$, i.e. the first bar corresponds to the average value the largest investment for every firm has as a share of total investment of that firm, the second bar to the average value of the second largest investment and so forth. Panel b) depicts the distribution of Gini coefficients of each firm's investment spending over the sample. Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

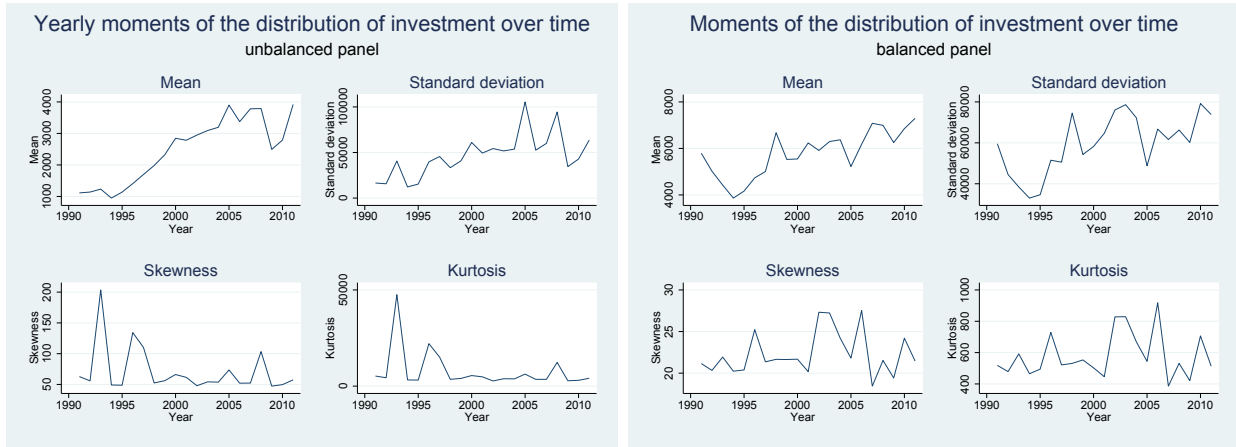
tribution of Gini coefficients of all firms then gives an impression of how this inequality is distributed across firms. The results are reported in figure 1.2b and illustrates the dispersion of investment spending of firms over time, thus confirming the substantial lumpiness that is contained in microeconomic investment spending.

1.2.2 Distribution of firm-level investment

The firm-level data allows examining the distribution of microeconomic investment more closely. I compute the first four moments of the cross-sectional distribution of microeconomic investment for every year and use it to construct time series for each moment. The yearly data is then interpolated by the method of cubic match to a quarterly frequency.

The yearly moments are depicted in figure 1.3a for the unbalanced and in figure 1.3b for the balanced panel, respectively.

Firm-Level Data and the Dynamics of Aggregate Investment: A Structural Factor-Augmented Autoregressive (SFAVAR) Approach



(a) Unbalanced panel

(b) Balanced panel

Figure 1.3: Moments of the cross-sectional investment distribution

Notes: Depicted are the first four moments of the firm-level investment distribution over time. Panel a) depicts the unbalanced, panel b) the balanced panel. Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Several interesting features emerge: First, all moments exhibit substantial variation over the considered time period.

Second, the time series for the four moments differ distinctly between the unbalanced and the balanced panel. Straightforwardly, balancing the panel reduces the absolute values for the three higher moments, as the variation in the data due to firms with more extreme, but uneven investment spending is removed. Contrary to that, the mean is substantially larger in the balanced panel, by a factor of approximately 2. Accordingly, it is largely small firms with corresponding (relatively) lower investment spending that drop out of the sample once it is balanced. While the standard deviations only decrease slightly when moving to the balanced panel, large reductions can be found in the skewness and the kurtosis. Since both exhibit positive values, this corresponds to a reduction in the right tail of the investment distribution, that is, some of the firms who drop out over time or enter later have – compared to the rest of the distribution – very high and singular investment spending. Combining this information with the increase in the mean, we see that the firms in the balanced sample invest less extremely, but on average more.

Third, comparing the moments for specific time periods directly provides additional informa-

tion for the underlying microeconomic dynamics of changes in aggregate investment. Looking at the Great Recession, we see the distinct reduction in the mean of the unbalanced panel in 2008. This reduction is far less distinct for the firms in the balanced panel and furthermore seems to occur only with a one year delay in 2009. Thus, an important feature of the observed decline in aggregate investment in this time seems to be the fact that firms dropped out of business, while firms in the balanced panel decreased investment much less. This may also aid in explaining the persistent decline in aggregate investment, as two different margins of microeconomic adjustment were changing at different times: First, regarding the extensive margin, firms dropped out of business and aggregate investment was reduced in 2008. But in a second step, in line with the intensive margin, the remaining firms adjusted their investment spending. This adjustment took time, thus reducing investment in 2009. This interpretation is also supported by the standard deviations. While we see a clear spike in the standard deviation in the unbalanced panel in 2008, this is not visible in the balanced panel.

Finally, though with a level difference, skewness and kurtosis are remarkably similar in their dynamics and seem to capture the same effects of the underlying distribution.⁴ The skewness of the underlying investment distribution measures its asymmetry and importance of its tail and thus the heterogeneity of the firms with respect to their investment spending. The kurtosis is also indicative of the importance of the tails of the distribution. Since the skewness is very high, both skewness and kurtosis measure the importance of the right tail of the distribution with large positive investments. Accordingly, high values of the skewness (and kurtosis) time series correspond to episodes in which the cross-sectional distribution of investment is relatively extreme in that it features a long right tail indicating that some firms invest considerable amounts while others may be more cautious. Conversely, low values of the third and fourth moments suggest firms' investment spending is relatively homogeneously distributed. Again, this aids in explaining the dynamics of aggregate investment in the Great Recession and its aftermath. In the unbalanced panel, we see a spike in the third

⁴ The correlation between the two moments is larger than 0.98 for both the unbalanced and the balanced panel.

and fourth moment of the investment distribution in 2008, whereas those moments are not particularly high in this year in the balanced panel. This corroborates the interpretation of the different means in the crisis described above. Since firms dropped out of the sample in the crisis, inequality of the investment distribution – measured by the third and fourth moment – increased in the unbalanced panel in 2008. Because those firms dropping out are not included in the balanced sample, we do not see a comparable increase in inequality there. The concept of granularity described above suggests the cross-sectional distribution of microeconomic investment and its changes over time to help explain the dynamics of aggregate investment. The following empirical analysis will examine the effects of the moments of the micro-level investment distribution more formally.

1.3 Dynamic factor model and SFAVAR

In standard vector autoregressive analysis, the vector y_t contains variables only. The disadvantage of this approach is that the number of variables K which can be included in the analysis is limited, as the number of parameters to be estimated increases quadratically with K . A possible solution to this curse of dimensionality is based on dynamic factor models (DFM), in which a small number of latent factors f drive the comovement of n variables over time. When employed in the context of time series variables, DFM thus allow distilling the common movement of a potentially large set of variables into a small number of factors, with the factor loadings characterizing the influence of the underlying variables on the specific factors (see, for example, Stock & Watson (2011), Breitung & Eickmeier (2006) or Bai, Li et al. (2012) for technical details on DFM). The factors can consistently be estimated by principal component analysis and „if N is sufficiently large, then the factors are estimated precisely enough to be treated as data in subsequent regressions.“ (Stock & Watson 2011). Therefore, they can be included as normal variables within a VAR framework. The resulting model is known as factor augmented VAR or FAVAR, a term introduced by Bernanke et al. (2005). Thus, the information of the set of time series can be incorporated in the analysis

without suffering from the curse of dimensionality. This framework has been employed for example by Buch, Eickmeier & Prieto (2014) or Mönch (2008).

Following Bernanke et al. (2005), the DFM can be written as

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t, \quad (1.1)$$

where X_t is a potentially high-dimensionally vector of underlying variables, F_t the latent factors and Λ^f the factor loading matrix relating the factors to the variables.

In this setup, the set of variables from which the factors are estimated also includes the original variables used in the VAR („VAR variables“), hence the term $\Lambda^y Y_t$ in equation 1.1. Doing so allows for the possibility that when using a large set of underlying variables capturing different economic concepts like economic activity, inflation pressure or other, these variables may be highly correlated with the VAR variables and thus not including the latter would affect the estimation of the factors. In my analysis, however, I extract the factors from single firm-level variables, e.g. financing costs or cash flow, and include just one factor in the FAVAR, which represents precisely this variable. Accordingly, all underlying variables included are relatively narrowly related to this concept alone. Therefore, I do not consider the set of macroeconomic VAR variables in the estimation of the microeconomic factor and modify equation 1.1 to

$$X_t = \Lambda^f F_t + e_t. \quad (1.2)$$

Including the extracted factors F_t from the dynamic factor model in equation 1.2 in an otherwise standard VAR model then yields a factor augmented VAR (FAVAR):

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \quad (1.3)$$

where Y_t is the vector of macroeconomic variables, F_t the vector of latent factors, $\Phi(L)$ a lag polynomial and v_t the error term.

As explained above, the factor model is applied sequentially to single firm-level variables, therefore ensuring that the resulting factors can be interpreted in a meaningful way: Esti-

mating the model on the cash flow of all firms will yield a cash flow factor, i.e. the main dimension of variation in the cash flow data across firms. Because the factor model is estimated on narrowly defined and thus relatively homogeneous variables, only few of the resulting factors can explain a large share of the variation in the data.

To assess the dynamic effects of firm-level variables on aggregate investment, I estimate two different types of models. First, following the outlined concept of granularity, I augment a standard macroeconomic SVAR with the moments of the underlying micro-level investment distribution. Second, I estimate the SFAVAR described in equation 1.3 with a weighted factor from the four different sub-groups of variables.

The following section describes the identifying assumptions imposed on the reduced-form FAVARs to recover the structural shocks.

1.4 Identification and estimation

The starting point of the empirical analysis is a standard reduced-form FAVAR(p) model of the form

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + u_t, \quad (1.4)$$

where $y_t = (GDP, investment, deflator, factor, interestrate)'$ is the vector of variables, A_i are coefficient matrices for $i = 1, \dots, p$ and u_t is the vector of reduced-form error terms. *GDP* refers to gross domestic product, *investment* to aggregate firm investment and *deflator* to the GDP deflator.⁵

The two variables *factor* and *interest rate* are both factors, forming the F_t vector in equation 1.3. Specifically, the variable *factor* refers to the weighted factor from either the firm-level cash flow, profitability, debt or financing costs. For each of the four variables a separate model is estimated. The *interest rate* is the first principal component from a separate dynamic factor model on different macroeconomic interest rates. The use of a set of interest

⁵ See sections 1.6 and 1.6 in the appendix for details on the variables.

rates allows to better capture the concept of „average borrowing costs in the economy“ compared to a single interest rate.⁶

The corresponding structural FAVAR(p) model is then given by

$$B_0 y_t = B_1 y_{t-1} + B_2 y_{t-2} + \dots + B_p y_{t-p} + \omega_t, \quad (1.5)$$

where $B_0^{-1} B_1 = A_1$, $B_0^{-1} B_i = A_i$, $i = 1, \dots, p$ and $B_0^{-1} \omega_t = u_t$. Recovering the structural model therefore requires knowledge of the instantaneous effects matrix B_0 and its inverse (the structural impact multiplier matrix), respectively. The covariance matrix of the structural errors ω is normalized to be the identity matrix, i.e. $E[\omega \omega'] \equiv \Sigma_\omega = I_k$. Accordingly, the following relation holds:

$$E[u_t u_t'] \equiv \Sigma_u = B_0^{-1} \Sigma_\omega B_0^{-1'} = B_0^{-1} B_0^{-1'}. \quad (1.6)$$

Given that Σ_u can be estimated through equation 1.4, $\Sigma_u = B_0^{-1} B_0^{-1'}$ then allows recovering the structural impact multiplier matrix B_0^{-1} and thus the identification of the underlying structural shocks ω_t .

1.4.1 Identification

To recover the structural factor shock from the reduced-form VAR, block-recursive short-run exclusion restrictions are imposed on the structural impact multiplier matrix B_0^{-1} relating the reduced-form and structural errors according to $u_t = B_0^{-1} \omega_t$.

The set of imposed restrictions is presented in equation 1.7.

$$\begin{pmatrix} u^Y \\ u^I \\ u^P \\ u^F \\ u^i \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} & b_{13} & 0 & 0 \\ b_{21} & b_{22} & b_{23} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{pmatrix} \begin{pmatrix} \omega^{O1} \\ \omega^{O2} \\ \omega^{O3} \\ \omega^F \\ \omega^i \end{pmatrix} \quad (1.7)$$

⁶ See section 1.6 in the appendix for details.

The assumptions employed can be summarized in three blocks as follows.

First, GDP, investment and the deflator in the first block do not react within the same quarter to changes in the interest rate, because it takes time for these changes to influence aggregate economic outcomes. Investment is subject to time-to-build constraints as described in Kydland & Prescott (1982), that is decisions affecting the capital stock of firms are implemented with a lag. Accordingly, aggregate investment will not react to changes in the interest rate instantaneously. By extension, the same argument holds for GDP, as its components like private consumption are also slow-moving variables and consumers will not instantaneously adjust their spending to changes in the interest rate. In the same vein, prices can not immediately be adjusted.

The second identifying assumptions is that the micro-level factor does not react within the same quarter to changes in the interest rate, because firm-level variables will not instantaneously adjust to changes in macroeconomic conditions like the overall interest rate in the economy.

Lastly, GDP, investment and the deflator are assumed to not react to the microeconomic factor shock within the same quarter, as all three macroeconomic variables should not react immediately to changes in microeconomic variables.

This set-up is a block recursive identification scheme following Christiano, Eichenbaum & Evans (1999) with the first block comprising GDP, investment and the deflator, the second block being the microeconomic factor and the interest rate representing the third block. Because the model is only partially identified, this identification scheme has the advantage of imposing only a minimal amount of exclusion restrictions and thus avoiding implausible assumptions that arise in a model with causal orderings based on a lower triangular matrix, for example the extensive implications for the form of demand and supply curves.

In addition, Christiano et al. (1999) show that the ordering of the variables within a block does not matter for the responses of these variables to identified shocks. This means in my case that the responses of the deflator and the real economic variables to the factor shock are recovered correctly, independent of the ordering of these variables. This implies

that, although the matrix B_0^{-1} is not lower triangular, it can still be constructed by a lower triangular matrix decomposition, because the additional elements b_{12} , b_{13} and b_{23} that would be restricted to 0 in such a decomposition are irrelevant for the response of the variables they are associated with.

These advantages of the block recursive identification scheme come at the cost of not being able to identify aggregate demand and supply shocks. However, the focus of this paper, to examine the effect of factors from specific firm-level variables on aggregate investment, can be achieved with the proposed identification scheme.

Note that in this setup two shocks are identified, the factor shock and the interest rate shock in the last column. As described above, the interest rate is constructed as a factor from different financial market interest rates in Germany and the shock can therefore not be interpreted as a monetary policy shock. It is a shock associated with financial markets that increases the overall level of interest rates in the economy. While this second shock is identified, the analysis will focus on the effects of the factor shocks.⁷

Identification of the structural shocks in the SVARs with moment is based on the same considerations described above for the SFAVAR, but including the second and the third moment of the underlying distribution of firm-level investment, respectively, instead of a weighted firm-level factor in separate models.

1.4.2 Estimation

Estimation of the models is carried out in several steps. First, the variables based on the balance sheet data are computed. Then the factors are estimated by principal component analysis from the firm-level data. To this end the data matrix is reshaped such that columns contain the combinations of variable times firm, with 21 yearly observations for each combination. Afterwards, the variables are standardized. Factors are then drawn separately from the subsets of the data containing all variable-firm-combinations for one variable. This procedure allows interpreting the resulting factors as summarizing the information for the

⁷ The results of the interest rate shock are presented in section 1.6 in the appendix.

respective variables across all firms. If I were to draw factors from the full data set, the dimensions of the resulting factor loadings matrix would be (number of variables*number of firms)x(number of retained factors). Accordingly, it would be highly unrealistic to interpret the resulting factors in a meaningful way. By drawing from the sub-sets of all variable-firm-combinations for just one variable at a time, I avoid this problem as the data set is more homogeneous and thus the corresponding factors readily interpretable. For all sub-sets I retain the first six factors, which together explain between 64.3% and 82.3% of the variation in the sub-sets, and compute a weighted average factor using the single factor's explanatory share as weight.⁸ The moments of firm-level investment are computed as the cross-sectional moments of the underlying distribution for each year.

Second, the yearly factors and moments are interpolated to quarterly frequency using cubic interpolation.

Third, the reduced-form FAVARs in equation 1.3 are estimated by OLS. GDP, investment and the deflator are included in year on year growth rates. Because the interest rate factor is non-stationary, with high values in the early 90ies and a negative trend over time, it enters the model in yearly differences to achieve stationarity. The same transformation is applied to the factors and moments. For the lag length I set a fixed number of lags a-priori rather than relying on information criteria, which have a downward bias and may invalidate inference in finite samples.⁹ As the variables of interest in the analysis are macroeconomic aggregates (e.g. investment), I impose four quarterly lags. The residuals \hat{u}_t are then used to construct the estimate for the reduced-form covariance matrix Σ_u .

Fourth, the structural impact multiplier matrix B_0^{-1} is computed. Since the identification scheme is block-recursive, this can be achieved by calculating the Cholesky decomposition of the estimated reduced-form variance-covariance matrix $\widehat{\Sigma}_u$.

From the estimate for B_0^{-1} I then compute the structural impulse response functions as well as 95% confidence intervals based on a residual-based recursive design bootstrap with 100000 replications.

⁸ Detailed results of the principal component analysis are presented in table 1.7 and figure 1.17 in section 1.6 in the appendix.

⁹ See Leeb & Pötscher (2005) and Leeb & Pötscher (2008) for an in-depth discussion of this problem.

1.5 Results and discussion

In this section I present the results from the different models, beginning with the SVAR augmented with the moments of the firm-level distribution of investment. Specifically, the standard deviation and the skewness are considered to investigate the effects of intra-distributional dynamics on aggregate outcomes, which are not captured by simple aggregation. In addition, I distinguish between the moments of the unbalanced and balanced panel of firms for a total of four model specifications. Then I turn to the analysis of microeconomic determinants of investment by introducing the results of the factor model. The factors are subsequently used in the SFAVAR models, for which impulse response functions and forecast error variance decompositions are presented.

1.5.1 Factors

Figure 1.4 depicts the yearly differences of the weighted factors resulting from the principal components analysis of the firm-level data. The weighted factors are constructed by summing up the first six extracted factors for each variable set using their respective explanatory share as weights. Because the factors are orthogonal by construction, each one represents a new dimension in explaining the variance in the underlying data. This approach thus ensures the inclusion of information contained in the higher order factors, while preserving their relative importance. Table 1.7 in the appendix contains the first six extracted factors for the variables in the analysis with details on the principal component analysis and their explanatory share. Note that the variables have been standardized before the principal component analysis. Therefore, the level of the factors can not be interpreted.

The first panel shows the weighted factor extracted from firms' cash flow. After decreasing initially and stagnating from 1998 to 2001, cash flow increased substantially in the economic recovery after the burst of the dotcom bubble. In the aftermath of the Great Recession cash flow decreased drastically, before bouncing back even stronger in the following recovery.

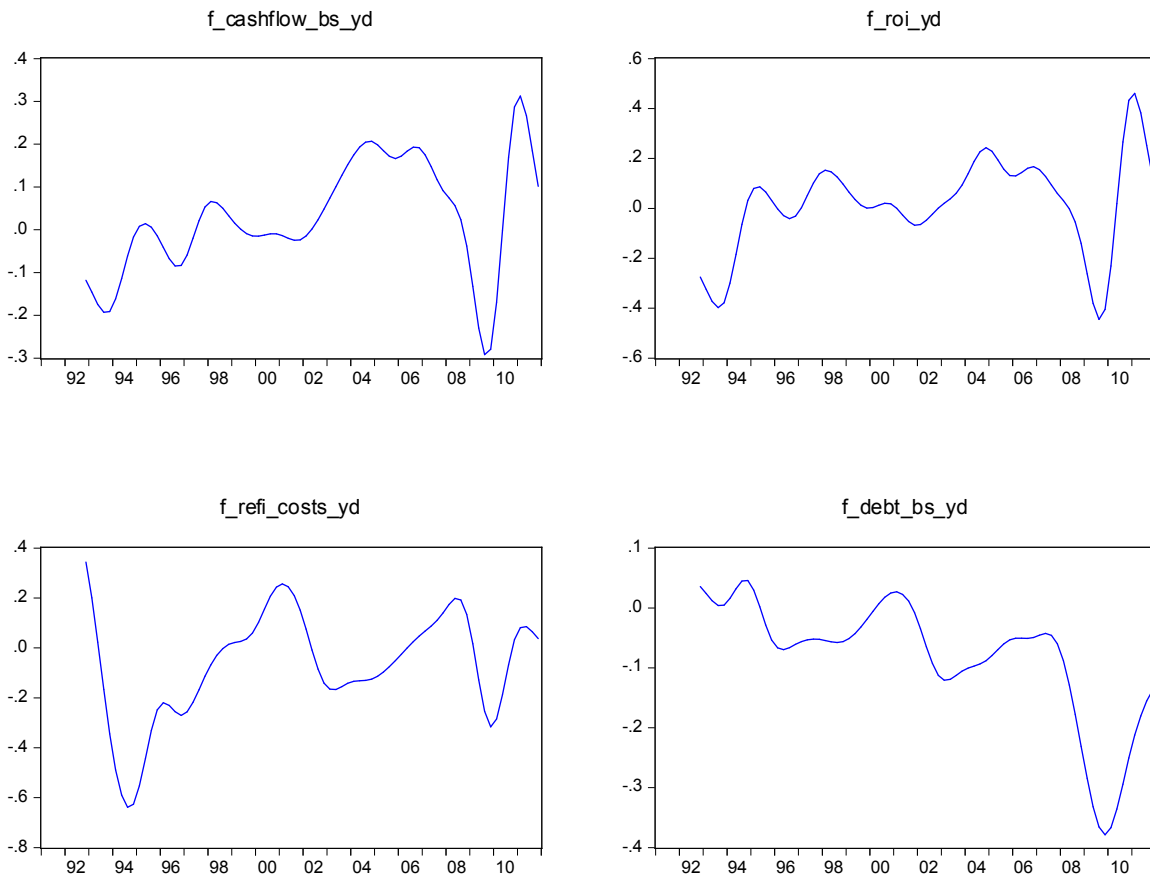


Figure 1.4: Weighted firm-level factors

Notes: Depicted are the year-on-year differences of the weighted factors for the four firm-level variables employed in the analysis. Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

The time series of firms' profitability is remarkably similar to the cash flow factor described above. This comes at no surprise, since both variables capture internal financing capabilities of firms.

The financing cost factor in the third panel exhibits a strong correlation with the German business cycle. It increased before the recessions in 2002/2003 (burst of the dotcom bubble) and 2008/2009 (Great Recession) and decreased after the respective downturns. In addition, the series depicts the pronounced time of decreasing financing costs in the first half of the 90ies associated with the strong lowering of the key interest rate by the Deutsche Bundesbank and the economic boom after the German reunification. This strong correlation with

the German business cycle is important to point out, since the financing cost variable is derived from balance sheet information of the firms and therefore measures average rather than marginal financing costs. However, the analysis suggests that the variable adequately captures the business cycle effects in the German economy.

The yearly differences in the debt factor in the fourth panel are mostly negative, indicating a slight deleveraging of firms in Germany over time. In the Great Recession firms reduced their liabilities substantially.

1.5.2 SVAR with moments

To assess the effects of the moments on the macroeconomic variables and especially aggregate firm investment, two outcomes are considered. First, impulse response functions provide an estimate of the effects of a shock to the moments on the other variables. Second, forecast error variance decompositions (FEVD) are computed to analyze the importance of the moment shocks for aggregate firm investment.

Figure 1.5 contains the result from the SVAR with the standard deviation of firm-level investment in the balanced panel. Based on this specification the standard deviation does not seem to have an important effect on real economic variables, as both the responses of GDP and investment are insignificant. This also holds for the reaction of the deflator and the interest rate, at least at the chosen significance level of 95%. The results do, however, point to a negative effect on the price variables, for the deflator about three years after the shock and around one and a half years for the interest rate. Taken together, the two results suggest that increased standard deviation has a mitigating effect on aggregate price pressure, but the results are not significant.

These relations are very similar when looking at the unbalanced standard deviation in figure 1.6. As in the balanced panel, a shock to the standard deviation does not affect the real economic variables, however, the responses of the financial variables are now different. The interest rate still reacts insignificantly, but without even an indication of a negative response as seen in the balance panel above. The only significant result is the negative effect on the price level, but this time much earlier, on impact for the first one and a half years.

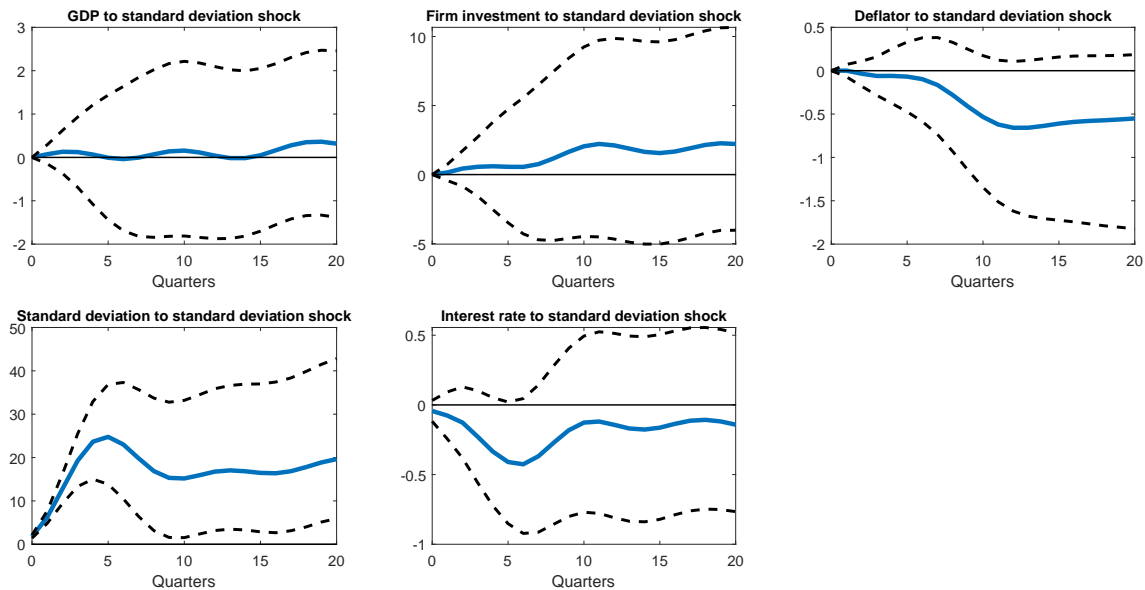


Figure 1.5: IRF standard deviation balanced panel

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Turning to the skewness, the results in figure 1.7 suggest that the third moment of the micro-level investment distribution has no effect on the variables in the system in the balanced panel.

This also holds when considering the results of the unbalanced panel in figure 1.7. The only exception is a very brief negative effect on the deflator on impact.

The analysis of the impulse response functions show no effects of the moments of the firm-level investment distribution on aggregate investment. This result is further strengthened by examining the forecast error variance decompositions of investment in table 1.2. Although the contribution of both the second and the third moment is larger when considering the balanced panel, the contributions are small for every specification.

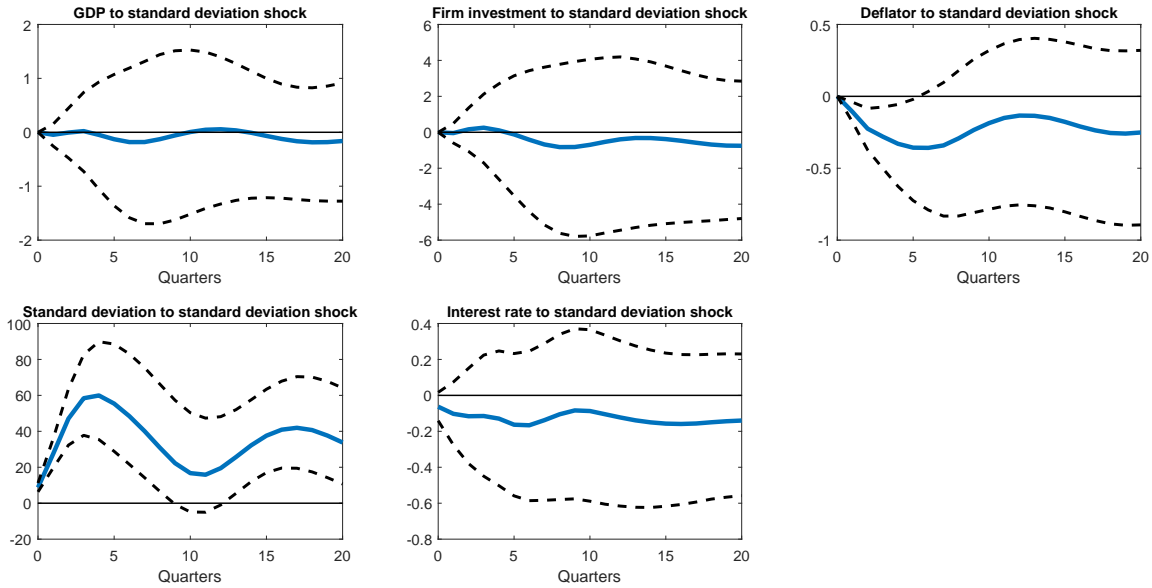


Figure 1.6: IRF standard deviation unbalanced panel

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Based on these results, shocks to the granularity as measured by changes in the skewness of the microeconomic investment distribution do not have significant effects on aggregate investment. The same insignificant results hold when considering the effects of the standard deviation as a measure of uncertainty.

1.5.3 SFAVAR

In this subsection I present the results from the different SFAVAR models, which each consist of the set of macroeconomic variables and one of the micro-level factors described above (cash flow, profitability, financing costs, debt). As with the SVARs with moments, I report both impulse response functions for an estimate of the effects of a shock to the factor on the other

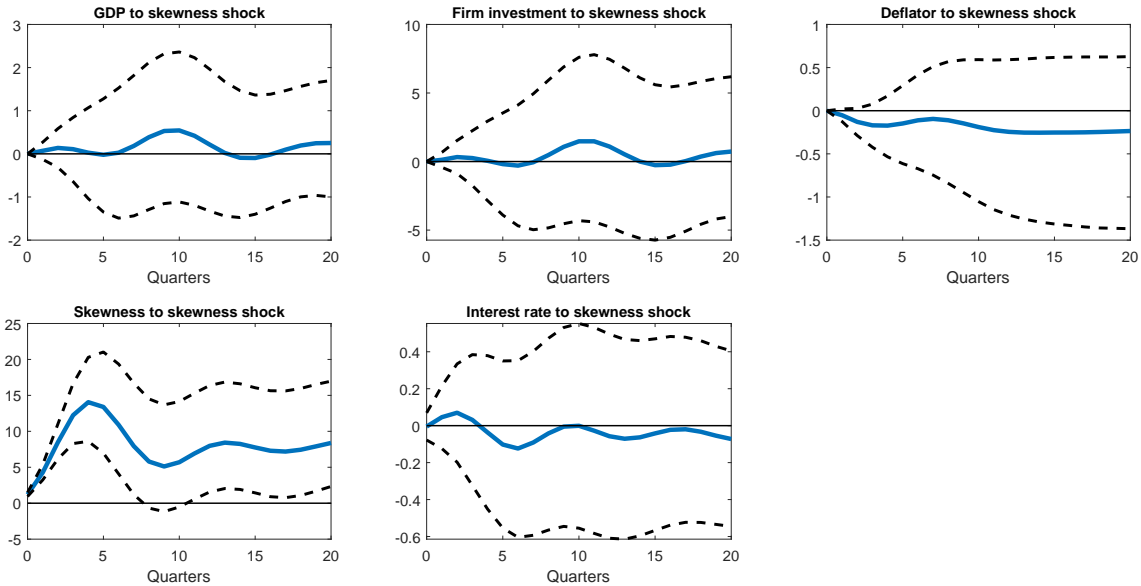


Figure 1.7: IRF skewness balanced panel

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

variables and forecast error variance decompositions to analyze the importance of the micro-level shocks for aggregate firm investment. Within the framework of the block-recursive identification scheme introduced in section 1.4 two shocks are identified, the factor shock and an interest rate shock. Because the factors are based on standardized variables from a large number of firms, the impulse response functions can not be interpreted quantitatively, but only qualitatively. Nevertheless, the responses of different variables to the same shock within the same model can be compared with respect to their relative size.

Cash flow Figure 1.9 depicts the impulse response functions from the SFAVAR with the weighted cash flow factor. A positive shock to this variable has a significantly positive effect on both real-economic variables. Comparing the two, we see that investment reacts stronger

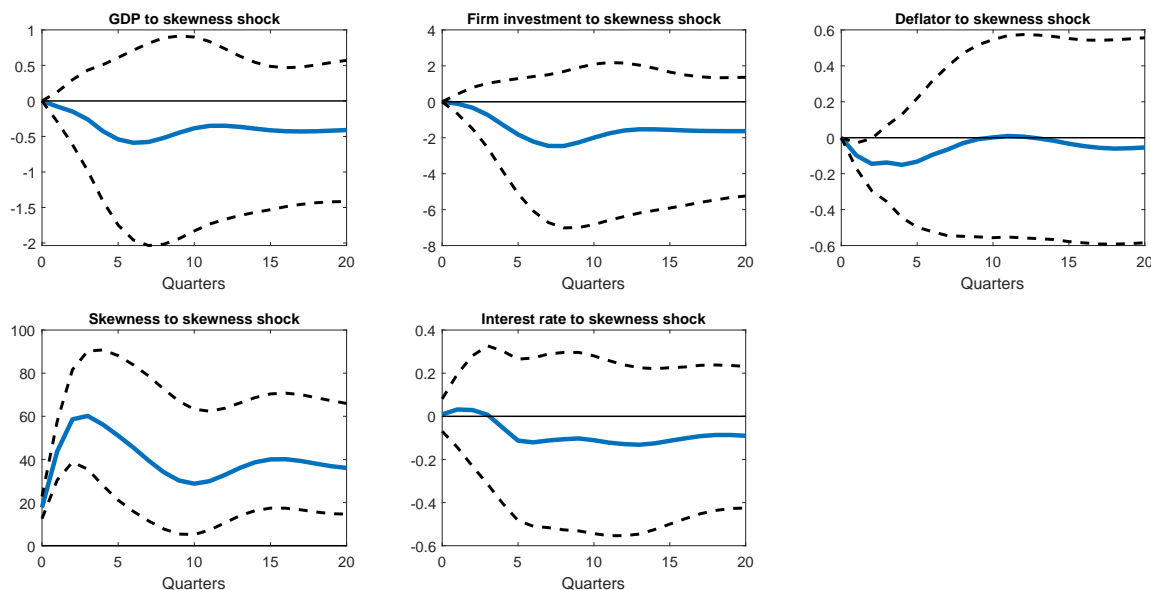


Figure 1.8: IRF skewness unbalanced panel

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

than GDP. This was to be expected, as the latter also contains components like private consumption, which should react less strongly to changes in cash flow and the resulting changes in firm-level investment. In addition, the effect on investment is longer-lasting than the one on GDP with a significant response for eight quarters.

We also observe a negative effect of the cash flow shock on the deflator after about three years and a positive effect on the interest rate: Taken together, the results suggests that a positive cash flow shock stimulates real-economic variables in the short-run and has a delayed dampening effect via increased interest rates and declining price level.

Profitability The results of a profitability shock in figure 1.10 are very similar to the ones observed above for cash flow: A significantly positive effect on the real-economic variables

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Table 1.2: FEVD of aggregate firm investment - contribution of moments

Horizon (quarters)	SD balanced	SD unbalanced	Skewness balanced	Skewness unbalanced
1	0	0	0	0
2	0.32	0.04	0.26	0.12
3	0.98	0.29	0.63	0.39
4	0.95	0.29	0.46	1.04
8	1.19	0.95	0.95	3.72
12	3.67	0.85	4.12	3.30
16	4.01	0.89	7.14	3.27
20	4.49	0.98	7.83	3.24
24	4.88	1.06	7.90	3.25
28	4.95	1.12	7.77	3.25
32	4.95	1.20	7.83	3.25
36	5.03	1.21	7.87	3.25
40	5.10	1.24	7.93	3.25

Notes: Tabled are the contributions of the moment shocks in the four different SVAR models based on the forecast error variance decompositions of aggregate investment.

with the effect on investment being stronger and lasting longer compared to overall GDP as well as a depressing effect on the price level and an increasing effect on interest rates. Given the similarities in the constructed factors for both profitability and cash flow shown in figure 1.4, this result is plausible and to be expected.

Financing costs The responses of the variables to a financing cost shock are depicted in figure 1.11. The effects on GDP and investment are largely insignificant, with the exception of a positive reaction in the first four (six) quarters for GDP (investment). This result is puzzling, as a positive financing shock implies higher financing costs and is expected to reduce real-economic output variables. Two implications of the financing cost variable are worth pointing out. First, the shock potentially contains both (credit) demand and supply shocks. However, the focus of this analysis is the effect of higher financing costs on aggregate investment. The underlying cause of these changes in financing costs (credit supply and demand) is therefore not important here. Second, because the variable is defined as firm-

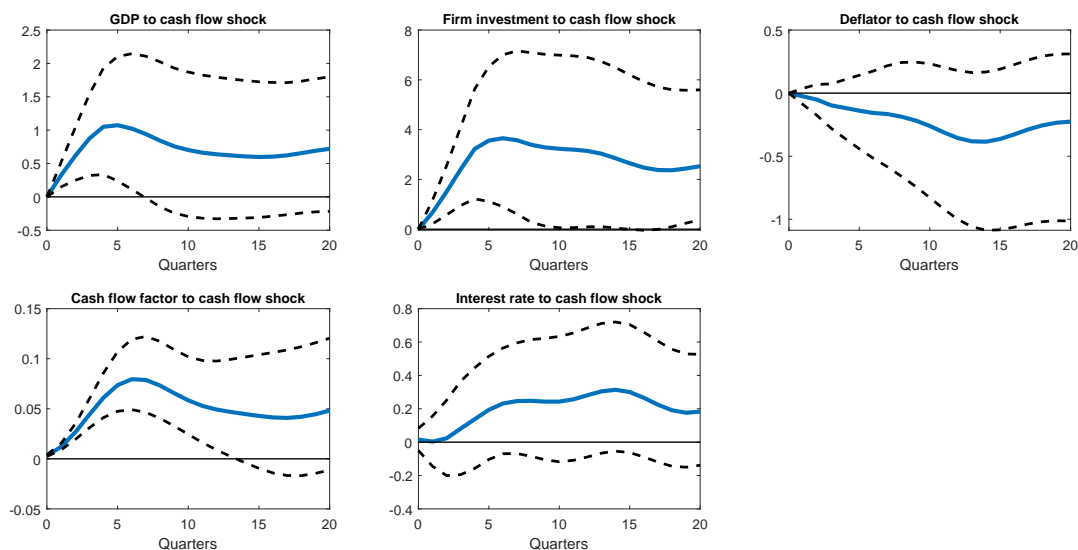


Figure 1.9: IRF cash flow

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

level interest payments divided by debt, it represents average rather than marginal financing costs. A sudden increase in marginal financing costs will, *ceteris paribus*, also raise average financing costs, but less strongly than the original increase.¹⁰ This dilution of actual interest rate changes may explain the largely insignificant responses of GDP and investment.

Turning to the financial variables, we see a pronounced negative effect of increased financing costs on aggregate prices. The response of the interest rate is insignificant.

Debt Lastly, figure 1.12 depicts the results of a sudden increase in firms' debt-to-balance-sheet ratio. Looking at the responses of GDP and investment we see a positive hump-shaped reaction of the real-economic variables. As observed for cash flow and profitability before, investment reacts stronger than GDP, again highlighting its importance for the dynamics of the business cycle.

¹⁰ This consideration abstracts from long-run macroeconomic developments. Because the variable of interest is average financing costs, it may be that even after the described increase in marginal financing costs average financing cost may still be lower if the current interest rate level is sufficiently lower than past ones in which the firms' also borrowed.

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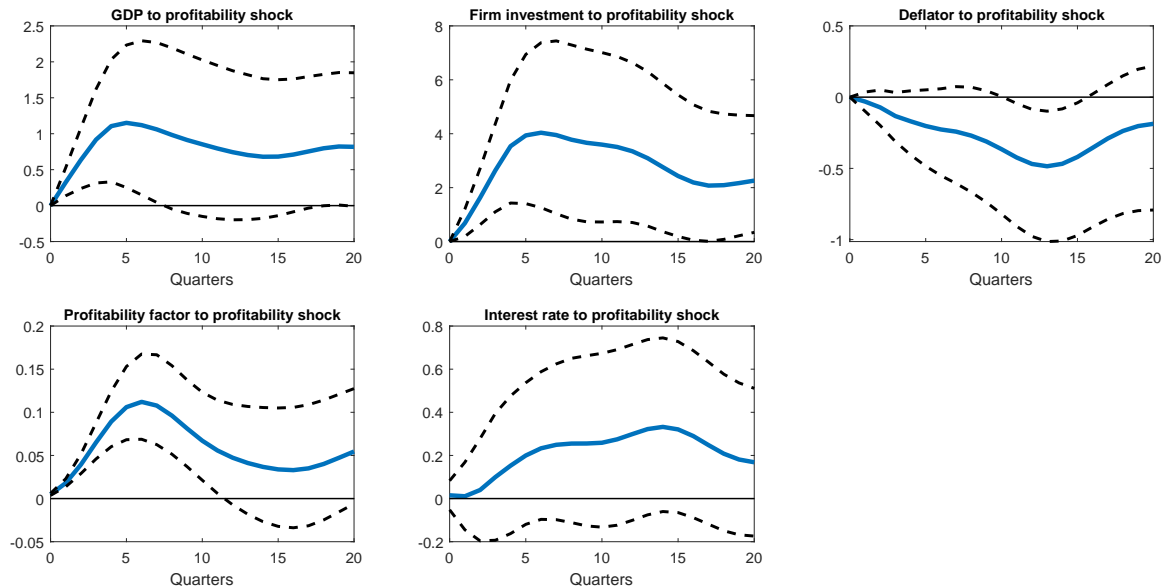


Figure 1.10: IRF profitability

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Note that since firm-level debt is measured as the debt divided by total balance sum, changes in both variables will influence the ratio. Accordingly, an increase could be due to firms extending their borrowing to finance new investment or a decrease in the balance sum due to equity losses. The results in this analysis point toward the first scenario of investment stimulating, expansive borrowing. This interpretation is also supported by the positive reaction of the interest rate. While higher interest rates alone may indicate higher lending premia by suppliers of credit, the combination of higher investment and interest rate suggest the expansionary scenario. The response of the deflator is insignificant.

While cash flow and profitability are measures for the internal financing possibilities of firms, increases in debt can be seen as external financing possibilities. The results presented in this

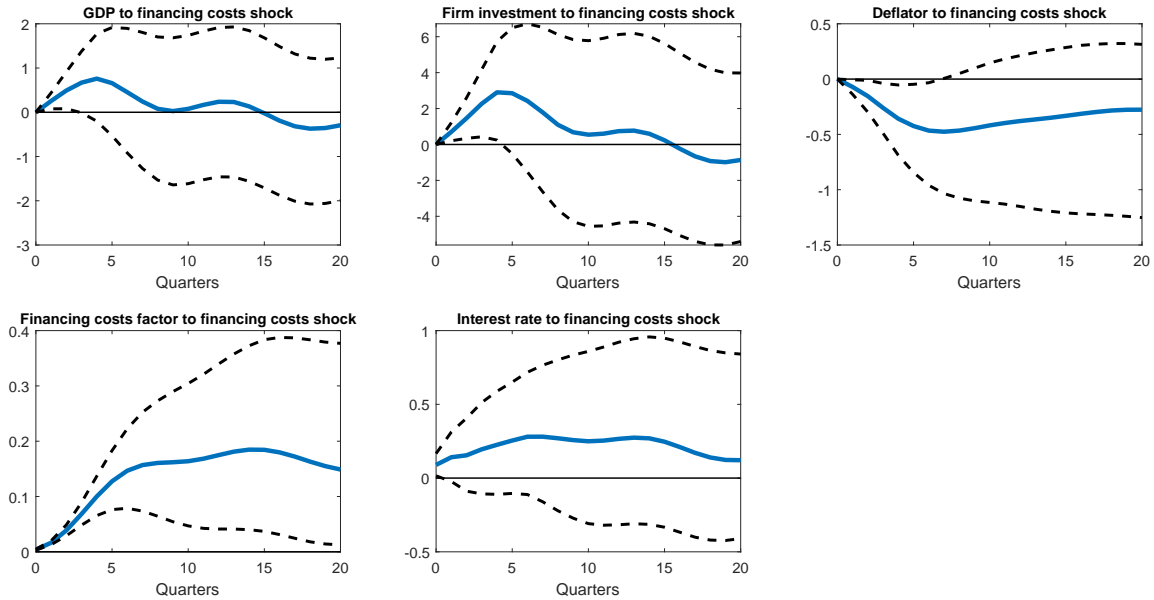


Figure 1.11: IRF financing costs

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

section show expansionary effects for both categories. However, there are also differences between the two. The cumulated reaction to cash flow and profitability for both GDP and investment is strongest after about six quarters and thus quicker than the response of the two variables to a debt shock, which has its strongest effect a year later, at around ten quarters. The impulse response functions depict positive reactions of investment and output to internal and external financing possibilities, while financing costs do not seem to have the expected negative effects. Accordingly, having access to capital may be more critical for firms' investment than the cost of this capital, suggesting that firms have profitable investment opportunities and do undertake them given sufficient financing.

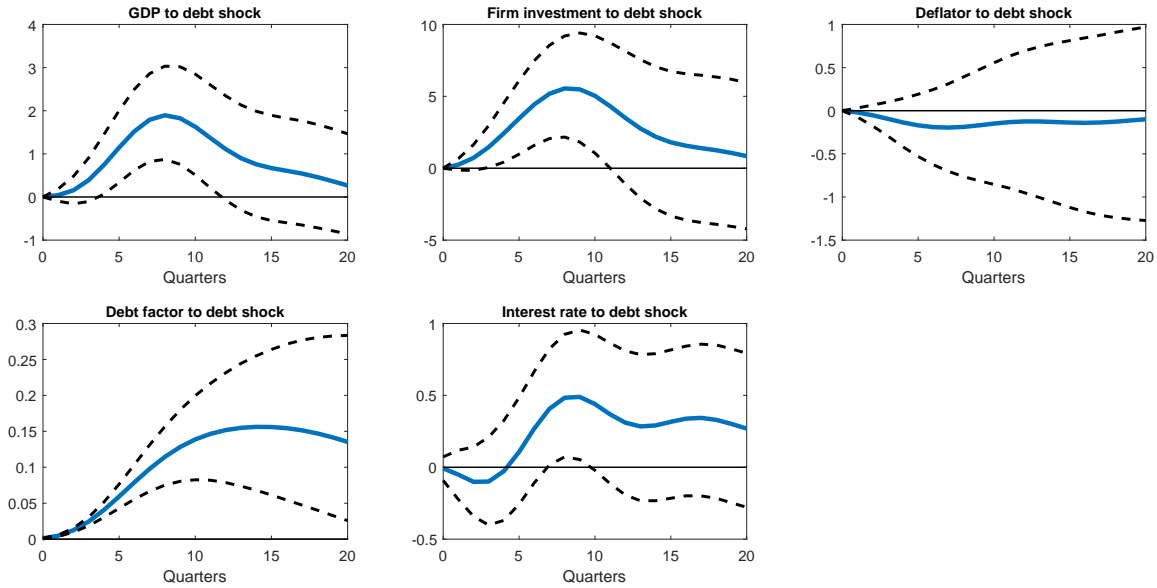


Figure 1.12: IRF debt

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Table 1.3 compares the contributions of the different micro-level factors in the respective models to the forecast error variance of aggregate firm investment for different horizons.

The long-run contributions of the factors are sizeable, ranging from 8.5% in the model with cash flow to 19.6% in the one with debt. In all models, firm-level shocks have important implications for aggregate investment. With a long-run contribution of almost 16% even financing costs play a substantial role, although the response of investment in figure 1.11 is almost completely insignificant.

The results described above point to important effects of shocks to the microeconomic factors on the dynamics of aggregate variables, especially investment, as I find both significant direct effects in the IRF and sizeable contributions of the shocks in the FEVD. However, this

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Table 1.3: FEVD of aggregate firm investment - contribution of micro-level factors

Horizon (quarters)	cash flow	profitability	financing costs	debt
1	0	0	0	0
2	4.95	5.43	5.48	0.68
3	8.32	10.44	8.57	2.37
4	10.03	13.14	10.17	5.64
8	11.30	14.88	12.76	20.06
12	9.46	11.68	13.83	17.28
16	8.70	11.23	13.84	20.85
20	8.71	11.15	15.76	19.81
24	8.63	10.86	15.90	19.84
28	8.54	10.87	15.82	19.49
32	8.53	10.90	15.81	19.46
36	8.52	10.86	15.82	19.50
40	8.52	10.91	15.83	19.55

Notes: Tabled are the contributions of the factor shocks in the four different SFAVAR models based on the forecast error variance decompositions of aggregate investment.

picture changes completely when excluding the Great Recession from the sample. Figure 1.13 compares the results of the SFAVAR models estimated over the full sample (until 2011Q4) to the results of the same models but with the estimation period restricted to 2007Q4. Each panel contains the IRF of aggregate investment to a shock to the respective microeconomic factor.¹¹ Full sample results are shown in blue, results excluding the Great Recession in red. Solid lines represent the median responses of the variables to the respective factor shock and 95% confidence intervals are shown as dashed lines.

In the full sample cash flow, profitability and debt all had a prolonged and significantly positive effect on aggregate investment while financing costs were somewhat surprisingly significantly positive as well. However, these relationships do not hold when only considering the time before the Great Recession, as the IRF for all four variables become insignificant. This also holds true for the responses of the other macro variables in the model in figures

¹¹ Full results for the estimation without the Great Recession are presented in figures 1.26 to 1.33 in the appendix.

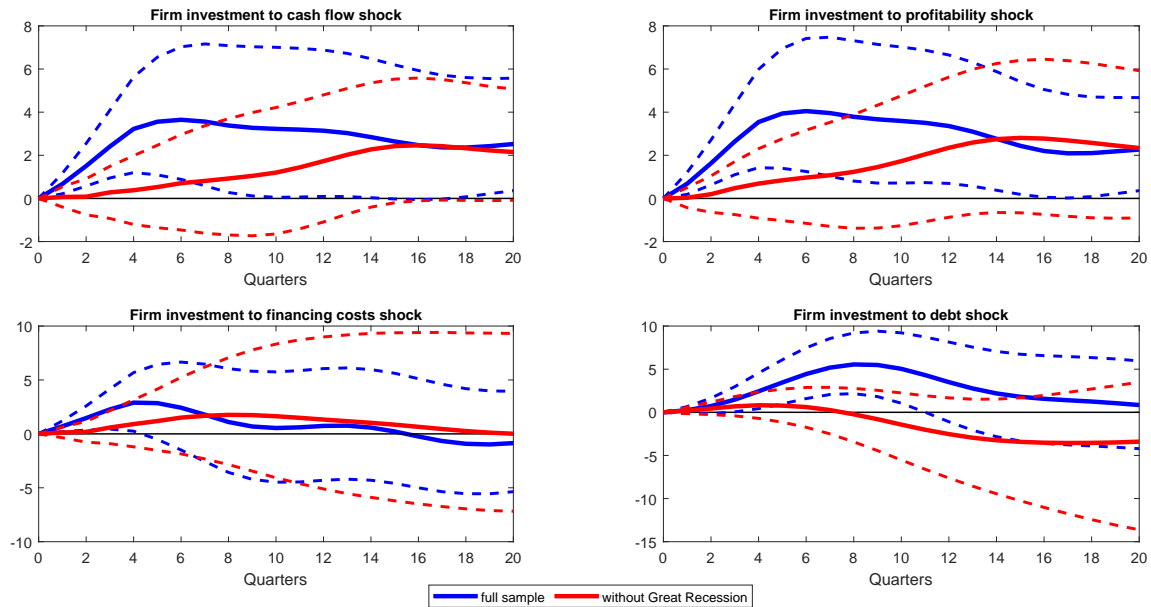


Figure 1.13: IRF comparison with and without the Great Recession

Notes: Depicted in each panel are the median and 95% confidence intervals for the full sample (blue) and excluding the Great Recession (red), based on 100000 bootstrap replications. Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

1.26 to 1.29 in the appendix. The microeconomic factors only seem to have a significant effect on aggregate variables in times of extreme economic situations, but do not provide additional information in „normal“ times.¹² This result is highlighted in the corresponding FEVD in table 1.4.

While the shocks to the factors explained 8.5% (cash flow), 10.9% (profitability), 15.8% (financing costs), and 19.6% (debt), respectively, of the forecast error of aggregate investment in the long-run when considering the full sample, the same shocks now only explain 4.9%

¹² I checked that the change in significance was not due to the fewer number of observations when restricting the sample to 1991Q1–2007Q4 by additionally estimating until 2011Q4, but starting appropriately later, thus keeping the number of observations the same.

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Table 1.4: FEVD of aggregate firm investment without the Great Recession - contribution of micro-level factors

Horizon (quarters)	cash flow	profitability	financing costs	debt
1	0.00	0.00	0.00	0.00
2	0.05	0.02	0.43	0.30
3	0.04	0.40	0.42	0.77
4	0.40	1.27	2.30	1.17
8	1.30	2.17	5.05	3.85
12	2.78	4.46	4.80	16.45
16	5.47	6.16	5.07	15.72
20	4.89	5.69	5.65	14.97
24	4.55	5.20	5.66	14.82
28	4.66	5.55	5.84	14.91
32	5.10	5.71	5.85	14.86
36	4.99	5.51	5.87	14.82
40	4.87	5.44	5.90	14.86

Notes: Tabled are the contributions of the factor shocks in the four different SFAVAR models based on the forecast error variance decompositions of aggregate investment when excluding the Great Recession (sample 1991–2007).

(cash flow), 5.4% (profitability), 5.9% (financing costs), and 14.9% (debt), respectively. So without the Great Recession all micro factors explain substantially less of the forecast error variance of aggregate investment. In addition, this explanatory share now only increases slowly with the horizon under consideration, whereas it rose more strongly already in earlier periods in the full sample.

These results are in line with findings from the literature in which the forecasting performance of DSGE models with financial frictions is assessed. Financial frictions in these models are commonly incorporated by introducing an external financing premium, a wedge between borrowing costs and return on investment which reduces a firm’s ability to obtain external funding. The firm-level variables considered in this analysis also measure a firm’s ability to obtain funding – internally through cash flow and profits and externally through capital costs and debt itself. Thus, the variables capture a comparable aspect of the financial frictions modelled in DSGE analyses.

Del Negro, Hasegawa & Schorfheide (2016) assess the forecasting performance of DSGE models with and without financial frictions in linear prediction pools with time-varying weights, allowing to compare the relative forecasting abilities of the two models over time. They find that the model with financial frictions has a better performance for output growth and inflation in times of financial stress, but not in normal times. In a similar vein, Holtemöller & Schult (2019) find that the incorporation of financial frictions improves DSGE model-based forecasts only during periods of financial crises.

1.5.4 Robustness

One assumption in the baseline identification scheme in equation 1.7 is the inclusion of the deflator in the block of macroeconomic variables. Since this variable is a price measure and as such may adjust faster to shocks than the real-economic variables GDP and investment, one might argue in favour of including the deflator in a block with the interest rate according to the following identification scheme:

$$\begin{pmatrix} u^Y \\ u^I \\ u^F \\ u^P \\ u^i \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} & b_{13} & 0 & 0 \\ b_{21} & b_{22} & b_{23} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & b_{34} & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{pmatrix} \begin{pmatrix} \omega^{O1} \\ \omega^{O2} \\ \omega^F \\ \omega^{O3} \\ \omega^{O4} \end{pmatrix} \quad (1.8)$$

Because deflator and interest rate are within the same block in this set-up, only the shock to the microeconomic factor in the third row is identified now, while the interest shock is not. However, the assumption that the deflator does not instantaneously react to the factor shock is no longer required. The IRF from re-estimating the baseline SFAVAR models with this alternative identification scheme are presented in tables 1.34 to 1.37 in the appendix. The results are unchanged compared to the baseline identification scheme.

1.5.5 Discussion

As described in the analysis, the micro-level data (factors and moments) are based on yearly balance sheet information of firms and are interpolated to the quarterly frequency of the macroeconomic variables included in the SFAVAR. The approach of interpolating lower frequency data to match the data frequency of the VAR model is not without precedent. For example, Bernanke, Gertler, Watson, Sims & Friedman (1997) interpolate real GDP to monthly frequency using the Chow-Lin (1971) procedure with monthly US industrial production and capacity utilization as indicator variables. Since I am dealing with variables that are unobserved (latent factors), I can not apply the same methodology. In any case, the potential issues arising from interpolation warrant some further discussion.

One possible way to think about the interpolation from low to high frequency and its implications is to view the transformed series as being affected by measurement error: In the quarterly series, every fourth observation corresponds to a true value from the original yearly series. The remaining quarterly values are constructed around these true values using cubic spline interpolation. The dynamics of the constructed series are correct and the same as the original yearly data, since the original yearly values are the basis for the algorithm. However, since the interpolation is based on pure statistics without considering external or economic information, the interpolated values will not be identical to the unobserved true quarterly series, but can be thought of as measured with an error. While theory provides an assessment of at least the asymptotic effects of measurement error in the case of OLS estimation, the effects are much less clear in the context of a VAR model. One consequence of measurement error may be an inflated volatility of the series. For example, Romer (1989) finds that measurement error is responsible for the higher volatility of gross domestic product in the US before WWII compared to more recent data. Higher volatility in turn has a negative effect on the precision of the estimation of VAR coefficients and statistics based on them such as impulse response functions. However, potentially serious issues like biases in the estimation remain unclear.

One way to deal with measurement error is to model it explicitly. Cogley & Sargent (2015) and Cogley, Sargent & Surico (2015) employ a non-linear state-space model in which volatil-

ities are allowed to change over time and measurement error is a latent variable. In this model the time series is composed of different data sources to cover the longest possible time span. The assumption in this type of model is that while the older part of a time series is noisy due to measurement error, the newest part of the data is not. This then allows estimating the measurement error process.

Amir-Ahmadi, Matthes & Wang (2016) extend this framework to VAR analysis with time-varying parameters and stochastic volatility. However, while their framework is closer to my analysis than the univariate model of Cogley et al. (2015), it still relies on the assumptions that the measurement of the same variable might have changed over time and that the latest source is free of error. In my case the time series and source are consistent over the sample, so a potential measurement error can not be estimated.

The potential problems from interpolating time series at a different frequency from other series in a model can be avoided altogether by incorporating every time series in their original frequency and estimating a mixed frequency VAR model, as in Kuzin, Marcellino & Schumacher (2011), Schorfheide & Song (2015) or Ghysels (2016). These models are cast in state-space representation and estimated using maximum-likelihood methods. To incorporate different frequencies of data, low frequency series are assumed to be in fact high frequency series with missing observations. Mixed frequency VAR models allow to include additional information from high(er) frequency variables. Foroni & Marcellino (2016) show that aggregating all variables to the lowest available frequency is inefficient and causes problems with respect to the identification of structural shocks, as the true model and thus the structural dynamics depend on the higher frequency variable. However, estimating the model with mixed frequencies and therefore more information solves these problems. Since I have data at different frequencies, this class of models could in principle be applied to the empirical analysis in this paper, but doing so would not yield any benefits. The advantage of mixed frequency VAR models is the ability to include additional information from high frequency variable in a model where the other variables are at a lower frequency. In my analysis, however, this set-up is reversed, as only the factor variable is at low frequency and the remaining variables are at a higher frequency. Therefore, there is no additional infor-

mation to be gained from incorporating the single variable (factor) at its original frequency. Estimating the model with a mixed-frequency approach thus does not provide an alternative either.

Besides the implication of higher volatility in the VAR, the theoretical assessment of the interpolation issue is not satisfactory and lacks concise implications for the empirical analysis at hand. In addition, neither of the two modelling approaches introduced above are applicable in my case. To get a better idea of the practical implications and potential problems, I therefore conduct a Monte Carlo simulation exercise similar to the approach in Forni & Marcellino (2016). To focus on the effects of interpolation, a bivariate quarterly VAR model with one lag as the data generating process is set up:

$$y_t = Ay_{t-1} + u_t, \quad (1.9)$$

where $y_t = (X_1, X_2)'$. The coefficient matrix A is chosen such that the resulting VAR system is stable, specifically, I set¹³

$$A = \begin{pmatrix} 0.2 & 0.8 \\ 0.7 & 0.2 \end{pmatrix} \quad (1.10)$$

The components of the error term $u_t = (u_t^{X_1}, u_t^{X_2})$ are independent draws from a normal distribution with $E[u_t^i] = 0$ and $Var[u_t^i] = (\sigma^i)^2$. The values for the standard deviations of the error terms σ^i are set to 0.5 for both, based on the average of their empirical counterparts in my analysis. I also verified, that the results of the simulation do not depend on the chosen levels.

With the coefficient matrix, the error terms and the model in equation 1.9 I can then simulate T observations for the vector of variables y_t using $y_0 = (0, 0)'$ as starting values. I focus on $T=80$ observations to match the number of observations in my empirical analysis.

With these observations I then estimate a bivariate VAR(1) model and compute and save the structural impulse response functions of X_1 to a shock in X_2 , assuming a causal ordering.

¹³ I also ran the simulation exercise with different parameter values, the results remained qualitatively unchanged.

This procedure is repeated $n=1000$ times. Afterwards, I obtain the median as well as the 5th and 95th percentiles of the impulse response functions as the baseline simulation results. To assess the effects of interpolating the factor series, I then modify the simulated factor series as follows: I only keep every fourth observation of X_2 (corresponding to the fourth quarter of a quarterly time series), pretending it to be yearly data. The hypothetical yearly series is then interpolated to quarterly frequency using the same cubic interpolation algorithm as in my empirical analysis. Combining X_1 and the interpolated X_2 , I then again estimate the VAR(1) model with this modified data set and compute the structural impulse response functions.

As before, I repeat the procedure $n=1000$ times and obtain the median as well as the 5th and 95th percentiles of the impulse response functions.

Comparing the simulation results from the first step (simulated quarterly factor series) and the second step (simulated yearly, then interpolated factor series) then allows assessing the effects of the interpolation on the estimation.

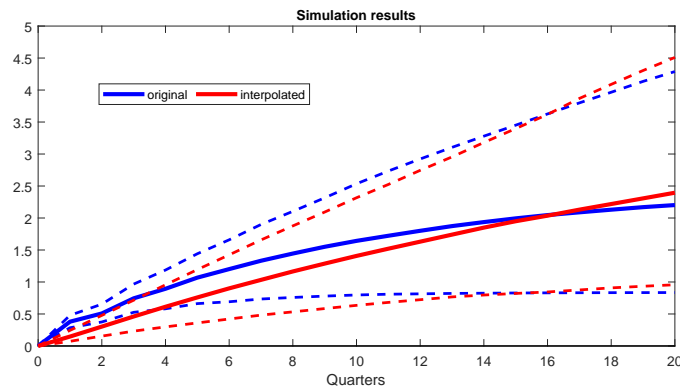


Figure 1.14: IRF simulation exercise

Notes: Depicted are the median and 95% confidence intervals for the baseline simulation (blue) and the simulation with interpolated data (red). Inference is based on 1000 Monte Carlo replications each.

Figure 1.14 depicts the results, the median of the cumulative impulse response function of X_1 to a shock in X_2 with 5th and 95th percentiles as confidence intervals.

As can be seen, the interpolation procedure does not cause a significant bias in the impulse response function, as the median responses are nearly identical. If anything, the response in the interpolated model understates the true response slightly in the earlier quarters of the horizon. Most importantly for the empirical analysis in this paper, the significantly positive response in the true model is correctly recovered in the interpolated model.

Examining the effect of the interpolation on the uncertainty of the results, we see that the confidence intervals essentially overlap for both models. Accordingly, the interpolation procedure does not seem to increase the uncertainty of the estimation.

To assess the robustness of the results from the simulation, I repeated the analysis for different coefficient matrices A in the VAR process and with a different level of the standard deviation of the error terms and found no qualitatively different results across specifications. In addition, I examined whether the effects of the interpolation depend on the volatility of the series in question by choosing different values for the standard deviation of X_2 and therefore changing the ratio of the standard deviations of the error terms $\sigma^{X_1}/\sigma^{X_2}$. The results suggest that for smaller values of σ^{X_2} , the interpolation induces a positive bias and thus overstates the true results. Conversely, when σ^{X_2} gets larger, the bias is negative. In both cases, the magnitude of the bias seems to depend on the size of the deviation of the ratio $\sigma^{X_1}/\sigma^{X_2}$ from 1. In terms of the uncertainty of the estimation, the results indicate that the confidence intervals of the interpolated model become wider for small values of σ^{X_2} , i.e. the interpolation has a negative effect on the precision of the impulse response functions for small values of the standard deviation of the error term of the interpolated series. However, the qualitative results, that is the significance of the responses, are recovered for all values of σ^{X_2} .

In summary, the Monte Carlo simulation suggests that the interpolated models recover the results from the original models very well. Most importantly, the qualitative results are unaffected and these are the focus of the empirical analysis in this paper, as the exact size of the impulse response functions can not be determined anyway due to the fact that the size

of the factor shock can not be recovered because of the standardization before the principal component analysis.

1.6 Conclusion and policy implications

In this paper I employ a data set on balance sheet information of German firms to examine two mechanisms through which microeconomic information affects the dynamics of aggregate investment. The first analysis focuses on the influence of microeconomic variables important for firm-level investment decisions, the second on the effects of granularity, captured by the moments of the underlying firm-level investment distribution. To assess whether the additional information contained in the micro-level data helps to better explain the dynamics of aggregate firm investment, I estimate factor models on firms' cash flow, profitability, financing costs and debt and augment macroeconomic SVARs with the resulting factors to analyze their effects on aggregate investment. Similarly, I include the second and third moments in the SVAR and estimate their effects on aggregate investment.

I find that the financing variables on the micro level do indeed have a significant impact on aggregate firm investment. A positive shock to firm-level cash flow, profitability and debt each significantly increases aggregate firm investment. The response of investment to a shock in financing costs is mainly insignificant, but it does exhibit a significantly positive effect in the first year that is puzzling. All four shocks explain a substantial part of the forecast error variance decomposition of aggregate investment. However, this effect only seems to matter in times of financial distress. In normal times the firm-level information does not help explain aggregate firm investment, as the response of aggregate investment is insignificant for all four shocks in this case. With respect to the second analysis, I find the effects of changes in granularity to not matter for aggregate dynamics.

Since firm variables can provide additional information for the dynamics of aggregate investment in times of financial distress, policy makers need to pay attention to the development of those variables. The results in this paper highlight the importance of assessing additional sources of information in times when financial distress is high. The effects of firm-level vari-

ables need to be taken into account when macroeconomic policy is conducted, for example in form of a monetary or fiscal stimulus. This may improve the impact of these measures or at least the prediction of their effects.

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Appendix

Ustan data set

From the Ustan data set I retain the observations regarding regular, yearly balance sheet information. While all sector classifications are represented, holdings are excluded because of their atypical balance sheets. Furthermore, I restrict the sample to cover the years 1991–2011. The starting point is chosen to avoid structural breaks in the data due to changes in the reporting framework in 1987 and the German reunification in 1990. The end point is chosen because after 2011 the number of firms in the data set decreased sharply. Truncation of the data then proceeds in two steps. First, impossibly high observations are discarded. Specifically, I drop observations if the share of current assets to the total balance sum is larger than 1 or if the share of fixed assets to the total balance sum is larger than 1. Second, because the data still contained observations with theoretically possibly, but unrealistically high values for certain variables, I compute the upper and lower 1% percentile of the cross-sectional distribution of the equity share (ratio of own funds to total balance sum) and of the share of profits to equity. Afterwards, observations above the upper 1% percentile and below the lower 1% percentile, respectively, are dropped. Inspection of the data revealed that this procedure sufficed to eliminate most of the outliers detected. This data set forms the unbalanced panel. As part of the analysis and for the estimation of the dynamic factor models, the data set is restricted to a balanced panel in which each the balance sheet information of a firm is observed over the entire sample period of 21 years.

Macroeconomic variables

Table 1.5: Variables summary

Variable	Description	Frequency	Transformation	Source
GDP	gross domestic product	quarterly	growth rate qoq	Destatis
firm investment	see details in section 1.6	quarterly	growth rate yoy	Destatis and own calculations
consumption	private consumption	quarterly	growth rate yoy	Destatis
interest rate	see details in section 1.6	quarterly	differences yoy	Deutsche Bundesbank and own calculations
deflator	GDP deflator	quarterly	growth rate yoy	Destatis

Aggregate firm investment

The aggregate firm investment used in the analysis is based on the frequently used fixed investment as reported in national accounts. However, this measure also contains investment of the government, which may follow different business cycle dynamics than the investment of private corporations. To account for this and focus entirely on private investment, I construct real aggregate firm investment by subtracting the part of fixed investment that is due to government activities. Figure 1.15 compares the series of aggregate firm investment to standard fixed investment. Aggregate firm investment is less volatile over the business cycle, so the government part in fixed investment seems in fact to have added to the cyclicality of investment.

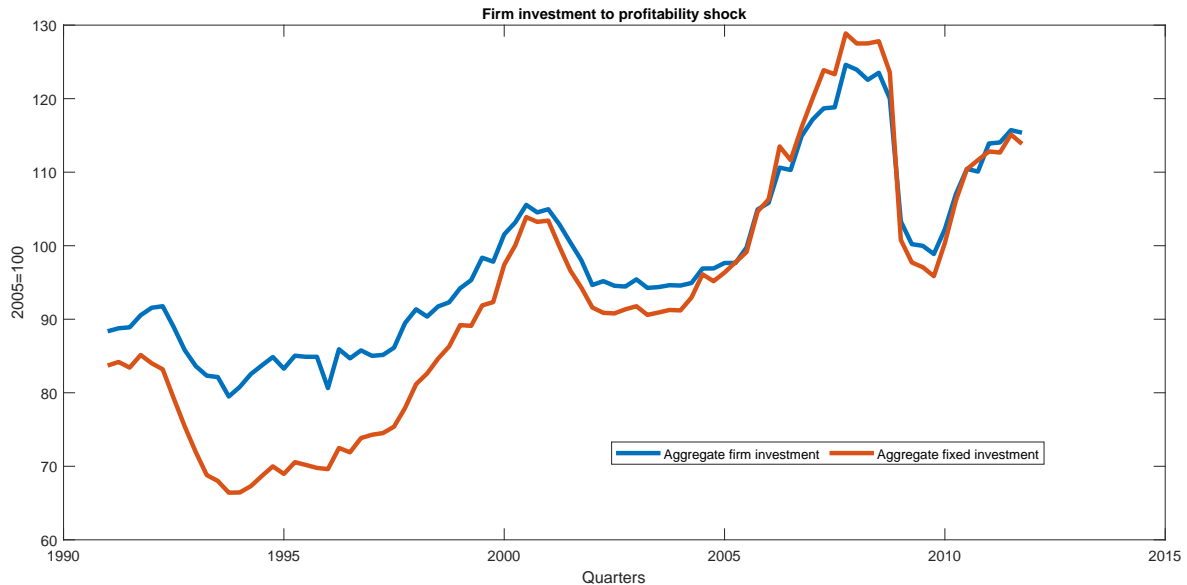


Figure 1.15: Standard aggregate fixed investment vs. firm investment

Notes: Depicted are aggregate investment and firm investment, which excludes the government part contained in normal aggregate investment.

Interest rate

The interest rate used in the analysis is a principal component from a dynamic factor model on different interest rates. The idea behind this is that one specific interest rate may not fully capture the concept of „average borrowing costs in the economy“. The factor model instead allows incorporating a variety of different interest rates to distil the underlying common component in one factor. The interest rates considered here are the average yield on bonds of non-MFI firms, the yields of several corporate bonds with average maturities between one and ten years, the twelve-month money market rate, yields of a ten-year government bond yield and the prime lending rate for Germany, with 14 interest rates in total. The variables are standardized and then principal component analysis is applied to estimate the factors. Figure 1.16 depicts the different interest rates and the first factor that is used in the analysis as „interest rate“. As one would expect, the series of the (standardized) interest rates are highly correlated: The extracted factor explains 95.22% of the total variation in the data. Detailed results of the factor analysis are given in table 1.6.

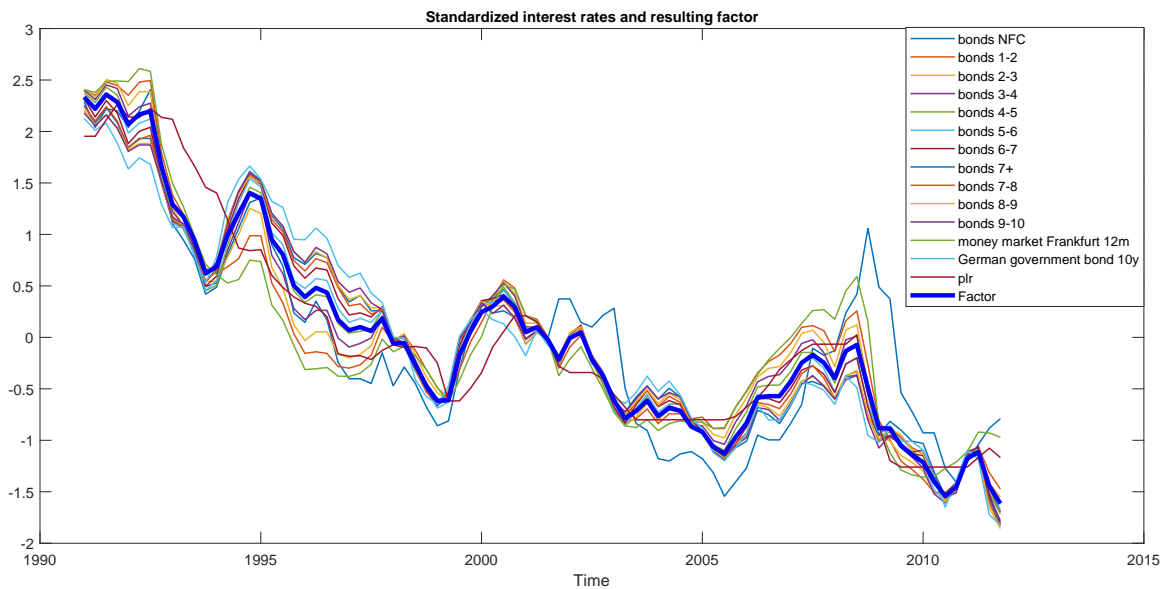
Table 1.6: Results of factor extraction interest rate

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	13.33072	12.91466	0.9522	0.9522
Factor2	0.41606	0.24920	0.0297	0.9819
Factor3	0.16687	0.09297	0.0119	0.9938
Factor4	0.07390	0.06793	0.0053	0.9991
Factor5	0.00597	0.00365	0.0004	0.9995
Factor6	0.00232	0.00080	0.0002	0.9997
Factor7	0.00152	0.00067	0.0001	0.9998
Factor8	0.00085	0.00026	0.0001	0.9999
Factor9	0.00059	0.00021	0.0000	0.9999
⋮	⋮	⋮	⋮	⋮
Factor14	0.00014	.	0.0000	1.0000

Notes: Tabled are the results of the principal component analysis of the interest rates.

Overall the interest rate level has a negative trend, beginning with relatively high values in the early 90ies and generally decreasing over the sample, with the decrease being more

Figure 1.16: Interest rates and interest rate factor



Notes: Depicted are the set of interest rates used in the factor analysis and the resulting first principal component as interest rate factor.

pronounced in the first half and slowing down a bit in the second half. Around this trend, however, one can see a strong correlation with the German business cycle, with the interest rate increasing during the economic expansions before major economic downturns in 2002/2003 and the Great Recession in 2008/2009.

Results of principal components analysis

I create and save subsamples for each of the four variables in the analysis (cash flow, profitability, refinancing costs, debt). Each subsample is then strictly balanced and reshaped such that each column corresponds to one firm's data of the respective variable and each row to one year. The variables are standardized and principal component analysis is conducted to estimate the factors. The results are depicted below. The first six factors are retained.

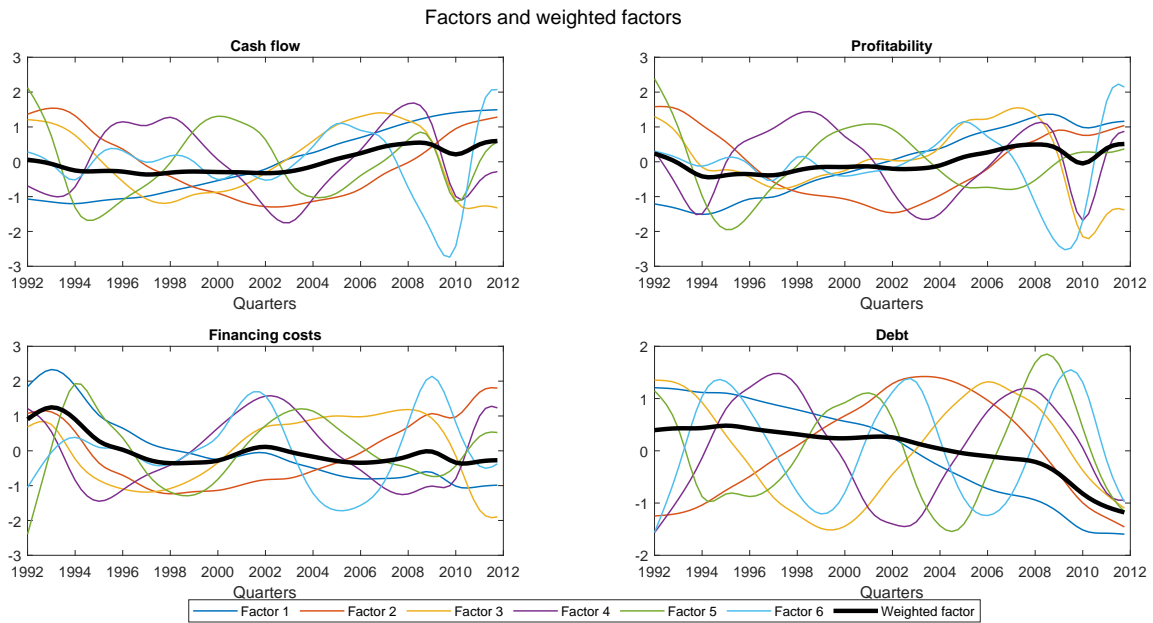
Table 1.7: Results of factor extraction

Factor	Eigenvalue	Difference	Proportion	Cumulative
cash flow				
Factor 1	443.34	241.48	0.2900	0.2900
Factor 2	201.86	74.29	0.1320	0.4220
Factor 3	127.57	32.96	0.0834	0.5054
Factor 4	94.61	9.89	0.0619	0.5673
Factor 5	84.71	17.86	0.0554	0.6227
Factor 6	66.85	8.40	0.0437	0.6664
profitability				
Factor 1	366.14	157.03	0.2395	0.2395
Factor 2	209.11	77.76	0.1368	0.3762
Factor 3	131.35	13.32	0.0859	0.4621
Factor 4	118.03	17.36	0.0772	0.5393
Factor 5	100.67	17.27	0.0658	0.6052
Factor 6	84.00	13.91	0.0545	0.6597
refinancing costs				
Factor 1	645.40	432.40	0.4227	0.4227
Factor 2	213.00	66.06	0.1395	0.5621
Factor 3	146.94	61.63	0.0962	0.6584
Factor 4	85.31	13.36	0.0559	0.7142
Factor 5	71.95	7.02	0.0471	0.7614
Factor 6	64.93	22.70	0.0425	0.8039
debt				
Factor 1	711.69	483.97	0.4655	0.4655
Factor 2	227.72	101.48	0.1489	0.6144
Factor 3	126.24	43.88	0.0826	0.6970
Factor 4	82.36	23.68	0.0539	0.7508
Factor 5	58.67	7.48	0.0384	0.7892
Factor 6	51.19	11.80	0.0335	0.8227

Notes: Tabled are the results of the principal component analysis for the sub-samples of firm-level variables used in the SFAVAR models.

Extracted factors

Figure 1.17: Factors and weighted factors



Notes: Depicted are the first six factors and corresponding weighted factor for the four firm-level variables used in the SFAVAR models. Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Results interest rate shock SVAR with moments

Standard deviation balanced

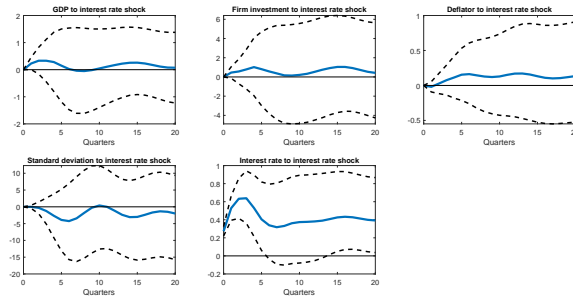


Figure 1.18: IRF standard deviation balanced interest rate shock

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Standard deviation unbalanced

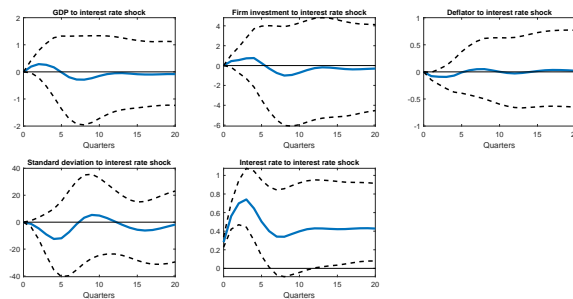


Figure 1.19: IRF standard deviation unbalanced interest rate shock

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Skewness balanced

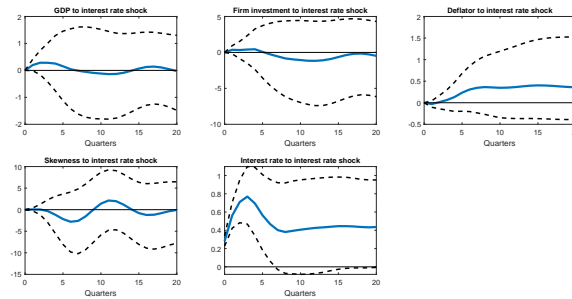


Figure 1.20: IRF skewness balanced interest rate shock

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Skewness unbalanced

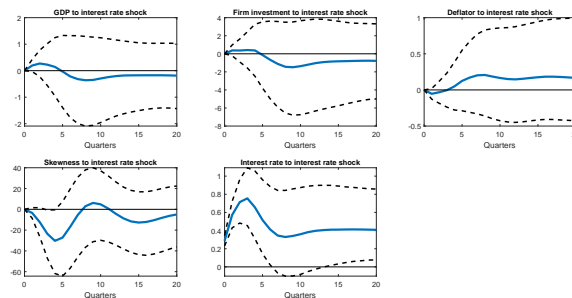


Figure 1.21: IRF skewness unbalanced interest rate shock

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Results interest rate shock SFAVAR

cash flow

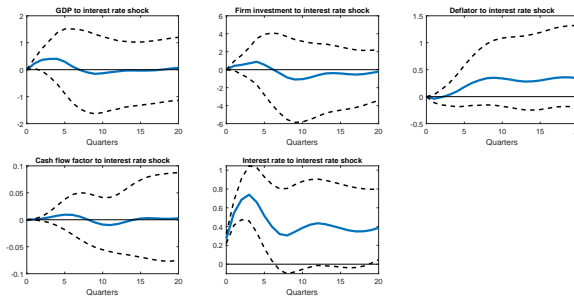


Figure 1.22: IRF cash flow interest rate shock

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

profitability

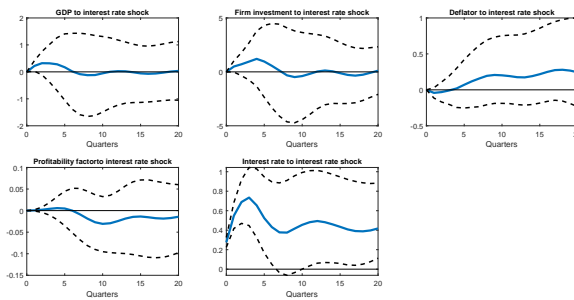


Figure 1.23: IRF profitability interest rate shock

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

financing costs

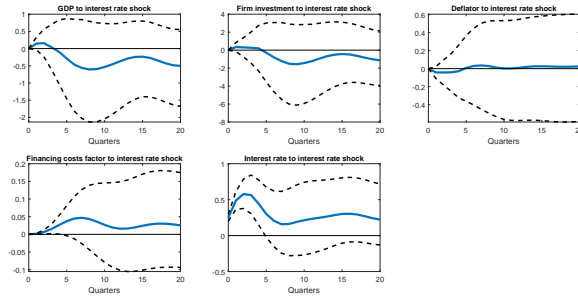


Figure 1.24: IRF financing costs interest rate shock

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

debt

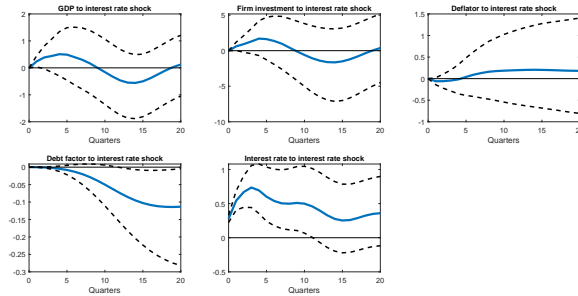


Figure 1.25: IRF debt interest rate shock

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Results excluding the great recession

Factor shocks

cash flow

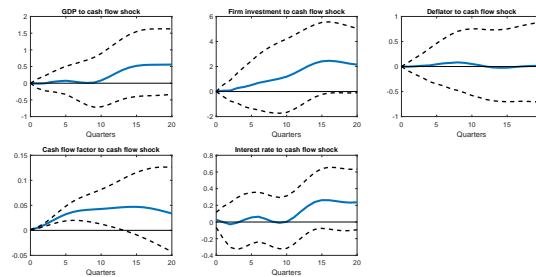


Figure 1.26: IRF cash flow without Great Recession

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

profitability

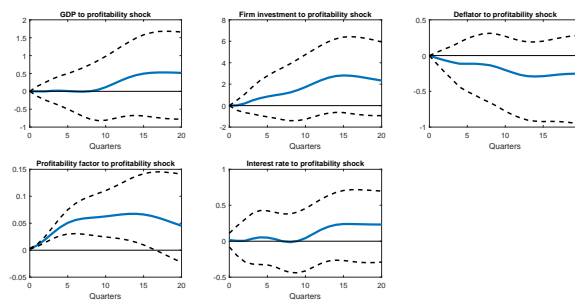


Figure 1.27: IRF profitability without Great Recession

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

financing costs

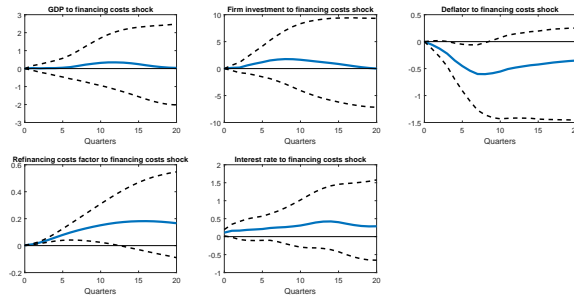


Figure 1.28: IRF financing costs without Great Recession

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

debt

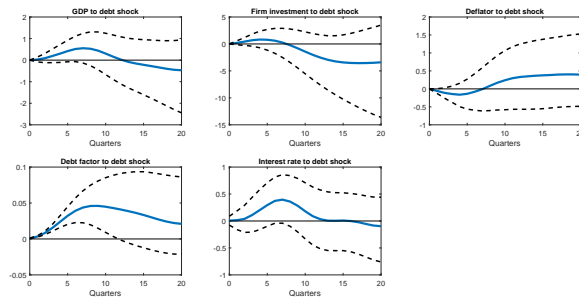


Figure 1.29: IRF debt without Great Recession

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Interest rate shocks

cash flow

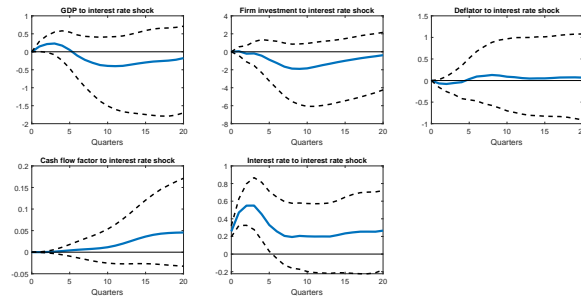


Figure 1.30: IRF cash flow interest rate shock without Great Recession

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

profitability

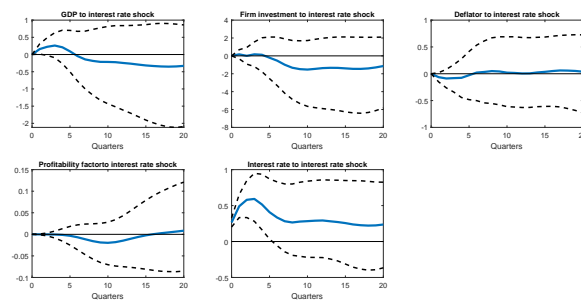


Figure 1.31: IRF profitability interest rate shock without Great Recession

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

financing costs

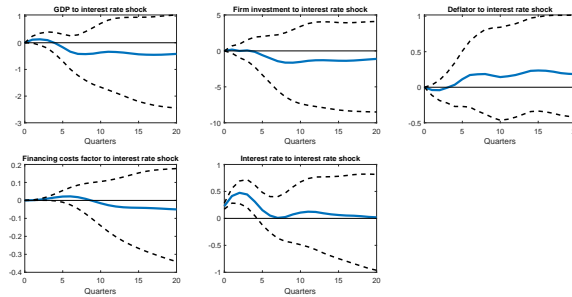


Figure 1.32: IRF financing costs interest rate shock without Great Recession

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

debt

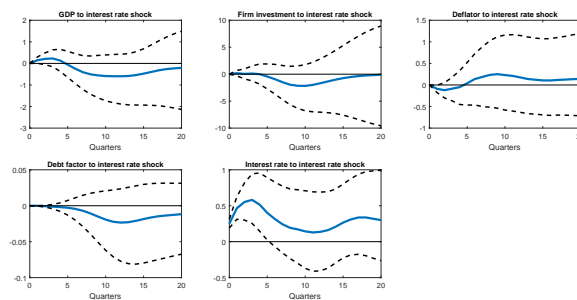


Figure 1.33: IRF debt interest rate shock without Great Recession

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Results alternative identification scheme

cash flow

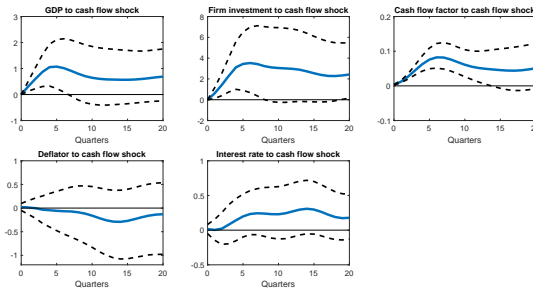


Figure 1.34: IRF cash flow alternative identification scheme

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

profitability

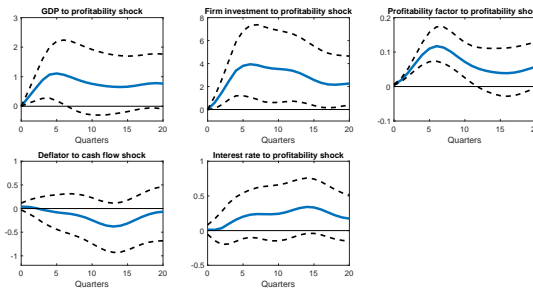


Figure 1.35: IRF profitability alternative identification scheme

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

financing costs

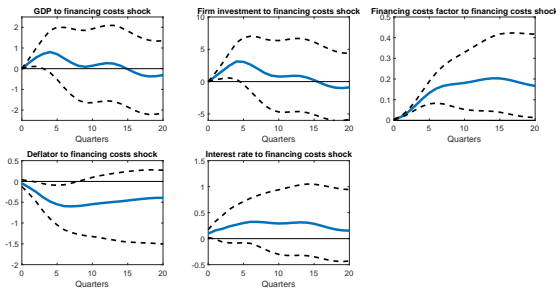


Figure 1.36: IRF financing costs alternative identification scheme

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

debt

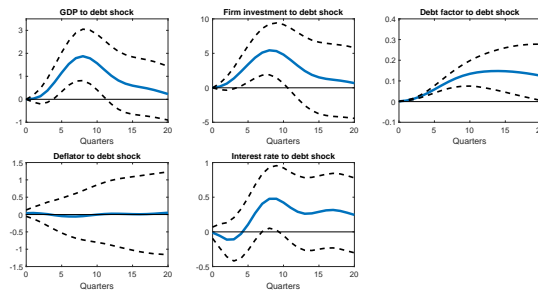


Figure 1.37: IRF debt alternative identification scheme

Notes: Depicted are the median and 95% confidence intervals based on 100000 bootstrap replications.

Source: Ustan data set of the Deutsche Bundesbank (Becker et al. 2020) and own calculations.

Chapter 2

Sovereign Stress, Banking Stress, and the Monetary Transmission Mechanism in the Euro Area*.

Abstract

In this paper, we investigate to what extent sovereign stress and banking stress have contributed to the increase in the level and in the heterogeneity of non-financial firms' refinancing costs in the Euro area during the European debt crisis and how they did affect the monetary transmission mechanism. Employing a large firm-level data set containing 2 million observations we are able to identify the increasing effect of government bond yield spreads (sovereign stress) and the share of non-performing loans (banking stress) on firms' financing costs in a panel model by assuming that idiosyncratic shocks to individual firms are uncorrelated with country-specific variables. Moreover, we estimate both sources of stress to have significantly impaired the monetary transmission mechanism between 2005 and 2013. This finding suggests that the ECB's asset purchase programs during that period have helped to improve firms' financing conditions in stressed

* Joint work with my supervisor Oliver Holtemöller

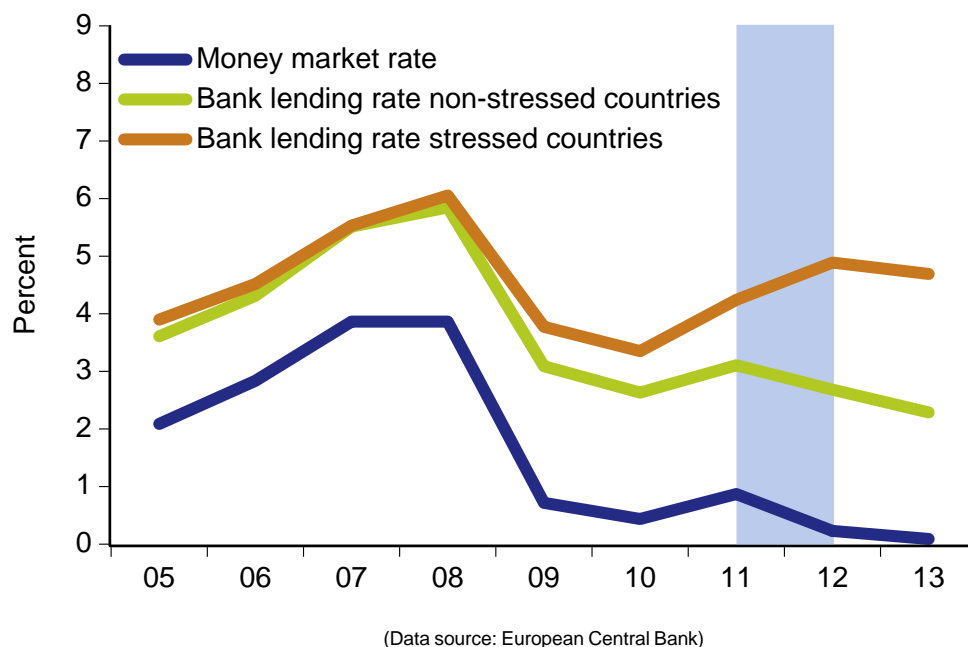
countries but that monetary policy transmission was still impaired due to the elevated level of banking stress in these countries.

2.1 Introduction

During the European sovereign debt crisis firms' financing costs have been disconnected from the key monetary policy interest rate in the Euro area. While bank lending rates of non-financial corporations are usually closely related to short-term money market interest rates, the spread between these two rates has considerably increased not only in the course of the worldwide financial crisis in 2008 (from below 2 percentage points to about 3.5 percentage points) but also in 2011 (to about 4 percentage points) when some Euro area countries have experienced sovereign debt crises. Furthermore, the heterogeneity of bank lending rates in various Euro area countries has increased. The difference between maximum and minimum country-specific spreads between short-term bank lending rates of non-financial corporations and the overnight money market rate has been equal to about 1 percentage point before 2008 and up to about 4 percentage points in 2012.

In this paper, we investigate to what extent sovereign stress and banking stress have contributed to this increase in the level and in the heterogeneity of non-financial firms' refinancing costs in the Euro area and how they did affect the monetary transmission mechanism. We use a large firm-level data set (Amadeus) in order to address two major challenges: Firstly, firms financing costs are of course not only driven by macroeconomic conditions like sovereign stress or banking stress but also by firm-specific characteristics. If the average riskiness of firms varies across Euro area countries this also affects the relation between monetary policy rates and bank lending rates. By using balance sheet data for non-financial corporations we control for firm-specific characteristics. Secondly, using firm-level data allows a causal interpretation of estimated effects of sovereign stress and banking stress on non-financial firms' financing costs by assuming that firm-specific shocks are uncorrelated with aggregate shocks. In addition, we also control for firm-specific characteristics that determine firm-specific risk premiums and for aggregate variables which are related to the aggregate interest rate level in

Figure 2.1: Bank lending rates stressed vs. non-stressed countries



the economy. We provide a more detailed discussion of the exogeneity assumption in section 3.5.

Figure 2.1 depicts aggregate bank lending rates for stressed and non-stressed Euro area countries¹ together with the overnight money market rate (Eonia). The dynamics of the rates in the two country groups are the same in the first half of the sample. However, the rates start to diverge in 2011, rising in the stressed and falling in the non-stressed countries. How can the change in the relation between monetary policy rate and bank lending rates be explained? A couple of recent papers show that sovereign stress in terms of elevated government bond yields may affect financing costs of non-financial corporations. Goodfriend and McCallum (2007), for example, introduce government bonds as collateral in an otherwise standard New-Keynesian macroeconomic model. Since sovereign stress reduces the price of government bonds their value as collateral is also reduced. As a consequence, lending costs of non-financial corporations increase in response to sovereign stress. Other papers like Gertler and Karadi (2011) stress the healthiness of banks as financial intermediaries. Decreasing

¹ „Stressed“ countries in our sample are Ireland, Italy, Spain and Portugal, „non-stressed“ countries Austria, Finland, France and Germany. See section 2.3.3 for details on this classification.

government bond prices reduce net worth and, therefore, capital of banks. This makes refinancing more expensive for banks themselves and is also transmitted to non-financial firms' financing costs. Bocola (2016) adds a precautionary motive for banks to the Gertler-Karadi framework and shows that sovereign stress may affect financing costs of non-financial firms through two channels: a risk channel and a liquidity channel. In this framework, the financing costs of non-financial firms depend both on their own productivity and riskiness and on the financial situation of the banks. In addition to sovereign stress, models of the Gertler-Karadi and Bocola type imply more generally that financing costs of non-financial firms depend on the financial situation of banks. Sovereign stress is by far not the only factor that may negatively affect net wealth of banks. An increase in the share of non-performing loans, for example, does also reduce net worth of banks due to the adjustment of the value of outstanding loans in banks' balance sheets. Therefore, both sovereign stress as indicated by elevated government bond yields and banking stress as indicated by the share of non-performing loans may affect the spread between bank lending rates of non-financial corporations and the monetary policy rate. Since government bond yields and the share of non-performing loans have become more heterogeneous in the Euro area since the European debt crisis, these factors may also explain the disconnection and the heterogeneity of firms' refinancing costs. This also implies a non-linearity in the effect of changes in the monetary policy rate on firms' financing costs: elevated stress levels may impair the monetary transmission channel from policy rates to bank lending rates.

We show (1) that corporate financing costs in stressed countries and in non-stressed countries in the Euro area moved in significantly different directions during the years 2011 and 2012, even after controlling for firm-specific characteristics, while they moved in the same direction before the sovereign debt crisis; that (2) sovereign stress and banking stress significantly increased corporate financing costs and thus help explain the observed disconnection between stressed and non-stressed countries; and (3) that both macroeconomic stress factors impaired the monetary transmission mechanism. While our three main results are in line with theoretical considerations and thus come at no surprise qualitatively, we are – to the

best of our knowledge – the first to quantify the exact effects on corporate financing costs and the monetary transmission mechanism.

The remainder of the paper is organized as follows. Section 2.2 motivates the importance of sovereign stress and banking stress for the analysis of firms’ financing conditions. Section 2.3 introduces the micro-level data used throughout the analysis and describes our measure of firms’ financing costs. Sections 2.4 and 2.5 then highlight the importance of sovereign stress and banking stress for firms’ financing costs and the monetary transmission mechanism and describe our measures for the two sources of macroeconomic stress. The empirical approach and the results are presented in section 3.5. Finally, section 2.7 concludes.

2.2 Theoretical channels of stress pass-through

Our approach of examining the effects of sovereign stress and banking stress on firms’ financing costs is motivated by the two channels proposed in Bocola (2016). He analyzes and estimates the pass-through of sovereign stress on firm borrowing rates through the balance sheets of financial intermediaries. His framework is built on the quantitative DSGE model with financial intermediation of Gertler and Karadi (2011), in which an agency problem between households and the financial intermediaries introduces a financial accelerator mechanism propagating shocks to the financial intermediaries. Below we will briefly sketch the main aspects of this mechanism and explain the extension introduced by Bocola (2016) as well as the resulting channels of influence on firms’ financing costs.

In the framework of Gertler-Karadi, financial intermediaries receive funds from households and lend to firms who use the credit to finance their investments. However, there exists an agency problem between the households and the financial intermediaries, because the bankers operating the financial intermediaries can divert a fraction of the deposits received by the households. Consequently, the latter require the former to fulfill an incentive constraint, according to which the gains of this infidelity can not be larger than the implied costs (households can force unfaithful bankers into bankruptcy). As a consequence, the maximum amount of deposits a banker is entrusted with – and thus his ability to finance firm credit – is

tied to his equity serving as collateral. It is in this vein that the agency problem introduces an endogenous constraint on the intermediaries' ability to lend to the real economy.

A shock to the quality of intermediaries' assets reducing their value therefore weakens intermediaries' balance sheet and decreases equity. Due to the leverage ratio constraint financial intermediaries will then demand less firm assets, i.e. credit to finance new investment. This in turn reduces firm investment and the price of firm assets held by banks, further weakening the intermediaries' balance sheets. As a consequence, the effect of the initial shock to the quality of intermediaries' assets is amplified and can trigger an economic recession.

Bocola (2016) extends the Gertler-Karadi framework by introducing government bonds held by the intermediaries. The balance sheet of a financial intermediary can thus be represented as in table 2.1:

Table 2.1: Balance sheet of a financial intermediary

Assets	Liabilities
Government bonds (B)	Deposits (D)
Loans to firms (L)	Equity (E)

In the model, an increased probability of sovereign default and thus higher government bond yields affect credit rates for firms via two channels. First, there is a direct effect through the balance sheets of the financial intermediaries: Rising yields reduce the price of government bonds held by the intermediaries, weakening their balance sheets (B). As a consequence, banks' net worth declines which in turn reduces their ability to obtain funding. The resulting increase in funding costs is passed down to the real economy in form of higher borrowing costs for firms. Second, if the probability of a sovereign default increases, banks anticipate potential losses on their bond holdings and thus tighter funding conditions in the future. In addition, holding firm assets in itself becomes more riskier for banks. Once the default occurs, all then constrained intermediaries will sell their firm assets, drastically reducing their value. This so called risk channel generates „a precautionary motive for banks to deleverage and to reduce their holdings of firms' claims.“ (Bocola (2016), p. 3).

Besides the direct effects of both sources of macroeconomic stress, we can also derive an indirect effect on firms' financing conditions because the monetary transmission mechanism depends on both sovereign and banking stress: In the model of Bocola (2016) sovereign stress affects the asset side of banks' balance sheet, because rising yields and thus declining prices of government bonds decrease banks' net worth, reducing their ability to obtain funding, resulting in an increase in borrowing costs for firms. In the monetary transmission mechanism from the central bank to firms, the pass-through of interest rates crucially hinges on the behaviour of the financial intermediaries, i.e. banks. Accordingly, both sovereign stress and central bank interest rate decisions affect banks' funding costs and therefore the interest rates they demand for lending to firms. In this sense, the outlined effect of sovereign stress constitutes a premium for banks for a given interest rate decision by the central bank. Consider a scenario in which the central bank reduces interest rates. This reduction will, through the banks and with a temporal delay, be transmitted to firms' borrowing costs, so the banks decrease lending rates. If during this process, however, sovereign stress is high, then the mechanism described above will take effect and induce the banks to increase their lending rates. As result, the pass-through of central bank interest rate decisions will be diminished. Since this diminishing effect will be higher for higher levels of sovereign stress, it follows that the level of sovereign stress affects the monetary transmission mechanism. Similarly, we derive the interaction effect between the monetary transmission mechanism and banking stress. The risk channel in the model of Bocola (2016) suggests that banks deleverage and reduce credit to firms because they are perceived as riskier. Accordingly, banks will demand a premium on credit to firms. In addition, higher risk may induce banks to increase their liquidity buffer in preparation for possible future negative shocks. Consider again the scenario in which the central bank reduces interest rates. If banking stress is high, the resulting increase in lending rates will counteract the expansionary monetary policy. As before with sovereign stress, the degree of the counteracting effect will be higher for higher levels of banking stress. Therefore, the level of banking stress affects the monetary transmission mechanism.

In conclusion, sovereign stress can reduce the banks' resources to finance firms and banks may be more reluctant to lend due to a precautionary motive. Thus, and in addition to sovereign stress, also banking stress is an important determinant in explaining changes in firms' financing conditions. Therefore, the model implies that the level of both sources of stress impacts the monetary policy transmission, as they directly influence optimal behaviour of financial intermediaries when lending to firms.

Related literature has examined specific aspects of the sovereign-banking-firm-nexus. Acharya, Drechsler, and Schnabl (2004) develop a model with interdependency between stress in the banking sector and sovereign risk. Gennaioli, Martin and Rossi (2014) in turn examine the effects of government defaults on the banking sector and private credit. Similarly, Correa, Lee, Sapriza, Suarez (2014) analyze the impact of sovereign credit rating downgrades on bank stock returns. And Brutti and Sauré (2015) show that cross-country bank exposures to sovereign debt of Euro area countries propagate sovereign risk. Focusing on sovereign risk and firm credit, Corsetti, Kuester, Meier, Müller (2013) argue that the costs of financial intermediation depend on sovereign risk and that higher government risk premiums therefore also increase the wedge between the risk-free rate and private borrowing costs. Moreover, Sandleris (2014) finds that sovereign defaults can reduce foreign and domestic credit to the private sector.

2.3 Data

2.3.1 Firm-level data

We use firm-level data from the Amadeus data set provided by Bureau van Dijk. It contains annual balance sheet data of a large number of firms in different countries, sectors and with different legal forms. Examples of recent use of this data set include de Almeida (2015), who uses Amadeus data to examine the relationship between the financing conditions of firms in several Euro area peripheral countries and sectoral inflation, and Egger, Erhardt

and Lassmann (2015), who look at the relation between firm-level productivity or quality of products and domestic sales and exports in France.

Our sample comprises non-financial corporations² from the following eight member countries of the Euro area: Austria, Finland, France, Germany, Ireland, Italy, Portugal, and Spain³, covering the time from 2004 to 2013. A firm is allocated to the country in which the firm is domiciled, according to the classification provided by Bureau van Dijk. We account for outliers in the data by applying the following two-step procedure: First, we compute and drop the bottom and top 2% percentiles of all micro variables employed. In addition, we then eliminate those remaining observations containing implausible ratios of balance sheet positions by imposing that fixed assets, long-term borrowed funds and short-term borrowed funds as a ratio of total balance sum, respectively, must be non-negative and can not exceed 1. For the case of the own funds to balance sum ratio the upper limit applies as well, whereas the non-negativity constraint is not enforced because own funds as measured in a balance sheet can in fact be negative.

From this balance sheet data we utilize seven variables which are relevant for determining the financing conditions of the respective firm (see Altman (2000), Altman, Iwanicz-Drozdowska, Laitinen and Suvas (2014) and the references therein). Table 2.5 in the appendix lists the variables used in the analysis and the exact definitions. While this parsimonious specification may not fully cover the financial situation of a firm in every single detail, we are confident to capture the most important financial aspects. To explain the change in firms' financing conditions the micro variables enter the regressions in differences. To better capture the effect of monetary policy on the firm level, we additionally include interaction terms between the levels of the seven micro variables and the change in the money market rate (Eonia). The variables described above are available for every country in our sample, thus allowing us to consistently estimate our specification across countries. Summary statistics of the variables are provided in table 2.6 in the appendix. Overall our balanced panel data set comprises 2.301.610 observations for 230.161 firms. Of the firms in our data set are 40.41% small

² We exclude financial corporations, that is firms with NACE sector classification from 6400 to 6700.

³ Due to insufficient numbers of observations, we exclude Belgium, Greece, Luxembourg and the Netherlands from the sample.

(turnover up to 1 Million Euro), 55.32% medium sized (turnover more than 1 Million Euro and up to 50 Million Euro) and 4.27% large (turnover more than 50 Million Euro). All non-financial sectors except agriculture and mining are represented.

2.3.2 Measuring financing conditions at the firm level

We measure financing conditions at the firm level by interest payments divided by the average of liabilities in the current and previous period and call this variable financing conditions indicator or simply financing costs R_{ijt} for firm i in country j at time t . The average of two consecutive end-of-year values is taken as proxy for the average amount of debt during the year. It should be noticed that this indicator does not represent marginal borrowing costs but rather average borrowing costs in a specific period. Therefore, changes in bank lending rates on new business are only slowly reflected in our financing costs measure.

Using the financing conditions indicator variable described above, we construct average financing costs for each country by aggregating the firm-level specific financing costs according to

$$\bar{R}_{jt} = \frac{1}{N_{jt}} \sum_{i=1}^{N_{jt}} R_{ijt}, \quad j = 1, \dots, J \quad (2.1)$$

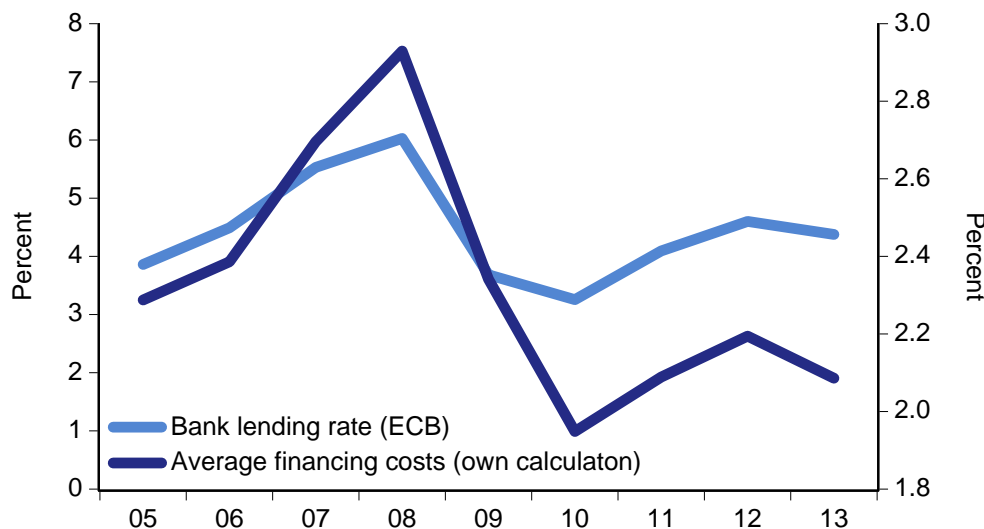
and

$$\bar{R}_t = \frac{1}{\sum_{j=1}^J N_{jt}} \sum_{j=1}^J \sum_{i=1}^{N_{jt}} R_{ijt}, \quad (2.2)$$

for the Euro area as a whole, where $J = 8$ is the number of countries, N_{jt} the number of firm observations for country j in period t , and R_{ijt} is the financing condition indicator for firm i in country j in period t .

To assess the reasonableness of the generated indicator, figure 2.2 depicts aggregate bank lending rates for non-financial corporations for the Euro area together with the average value of the financing conditions indicator for each year in the Euro area as a whole.

Figure 2.2: Financing conditions indicator and aggregate bank lending rate

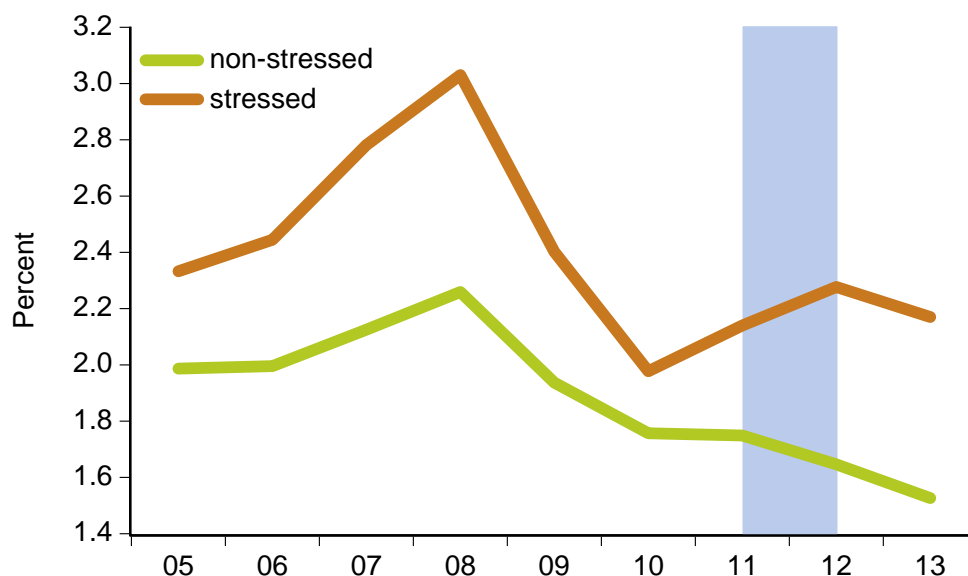


Notes: Bank lending rate denotes the short-term bank lending rate as published by the ECB (left scale) and the financing conditions indicator constructed from our individual firm data (right scale).

As can be seen, there are differences in the levels, but the dynamics of both time series are very similar.⁴ Comparable results also hold if we examine the individual countries separately (see figure 2.8 in the appendix). Therefore, the aggregated micro-level data and aggregate bank lending rates capture the same underlying dynamics. Financing costs for firms started rising in 2005 and reached a peak in 2008 before decreasing in 2009 and 2010. Afterwards, rates rose again in the wake of the European debt crisis. In conclusion, our constructed financing conditions indicators is a valid proxy for the dynamics of micro-level financing costs.

⁴ One potential reason for the difference in levels is the fact that liabilities on the firm level contain provisions which are not directly associated with interest payments. Positive provisions therefore lead to an understatement of firms' financing conditions according to our measure.

Figure 2.3: Firms' financing costs in stressed vs. non-stressed countries



Notes: Interest payments in relation to total liabilities. Sources: Bureau van Dijk and own calculations.

2.3.3 Firm-level financing conditions in stressed and non-stressed countries

The classification of countries into the two subgroups stressed and non-stressed is based on the respective country's government bond yield: Those countries with yields above the Euro area average are labeled „stressed“ (Ireland, Italy, Spain and Portugal), whereas those with lower yields are labeled „non-stressed“ (Austria, Finland, France and Germany).⁵ Applying this classification to our measure of firms' financing costs constructed above we find in figure 2.3 the same diverging development for the two subgroups in 2012 considering micro data as we observed before with aggregate bank lending rates (figure 2.1) in section 3.1: Rates rose in the stressed and fell in the non-stressed countries. In addition, this difference in development can already be observed in 2011. That is, based on our firm-level data, stressed and non-stressed countries exhibited diverging financing costs in the two years 2011 and 2012.

⁵ This corresponds to the classification in Corsetti et al. (2013)(although they consider some additional countries which are not contained in our sample) and to the sample of countries with a sovereign debt crisis in Knedlik and von Schweinitz (2012).

Table 2.2: Descriptive statistics of micro-level variables per country

Variable	Statistic	AT	DE	ES	FI	FR	IE	IT	PT	Total
cashflow	mean	10.2	8.8	6.0	12.5	9.5	6.2	4.9	6.7	5.9
	sd	8.4	7.3	7.3	10.1	8.1	7.8	6.2	7.2	7.0
	median	9.3	7.4	5.0	11.4	8.5	5.4	3.7	5.6	4.7
fassets	mean	40.7	44.4	42.7	51.0	31.3	46.1	31.1	33.3	35.5
	sd	28.3	29.0	28.1	27.4	24.8	31.7	27.4	24.1	27.9
	median	35.9	41.1	39.6	53.4	24.2	44.4	23.0	29.3	29.2
ltbfunds	mean	13.8	35.4	21.3	28.5	11.5	17.7	20.4	17.3	19.9
	sd	11.8	22.1	20.8	20.4	14.1	20.5	18.5	19.0	19.3
	median	10.5	31.8	15.3	24.8	6.4	9.8	15.2	11.5	14.2
stbfunds	mean	50.9	28.0	40.1	33.9	50.0	34.0	53.7	47.4	48.0
	sd	22.1	22.5	23.4	18.5	19.9	22.9	24.0	22.1	24.2
	median	53.5	23.8	38.4	31.6	49.9	28.8	55.6	46.8	48.2
refinancing costs	mean	1.7	2.8	2.6	2.7	1.8	2.2	2.3	3.0	2.4
	sd	1.4	1.9	1.7	1.6	1.4	1.7	1.6	1.9	1.7
	median	1.4	2.6	2.3	2.5	1.5	1.8	2.0	2.7	2.1
ofrentability	mean	14.8	11.9	5.9	12.9	14.6	6.6	4.8	5.5	6.4
	sd	31.0	24.3	25.1	31.6	26.5	22.4	29.6	23.8	27.8
	median	11.9	8.1	5.0	12.7	12.6	6.3	4.0	4.8	5.3
ofratio	mean	35.1	36.6	38.6	37.5	38.5	48.4	25.9	35.4	32.1
	sd	20.1	19.9	23.0	21.0	18.8	23.9	20.2	18.8	22.0
	median	31.7	34.2	35.9	36.4	37.3	48.4	20.8	32.9	28.3
roi	mean	5.2	4.0	2.1	5.3	5.3	3.2	1.5	2.1	2.2
	sd	7.7	6.2	6.4	8.4	7.3	7.6	5.3	5.7	6.1
	median	4.0	2.7	1.5	4.3	4.5	2.6	0.6	1.4	1.2

Notes: All statistics in percent, i.e shares (see table 2.5) are multiplied by a factor of 100.

While insightful, the graphical analysis of aggregate measures can not answer the question whether the differences in observed outcomes are based on country-specific variables or on differences between the examined country groups with respect to the underlying micro-level data. If these were heterogeneous across countries, we would also expect financing costs to be different. To assess potential differences across countries, table 2.2 provides summary statistics of the (aggregated) micro variables used for each country.

Although the differences are small for many variables, they are substantial for some, especially with respect to borrowed funds, both long- and short-term, own funds rentability and the return on investment. The latter two are pronouncedly lower in the group of stressed countries (Spain, Ireland, Italy and Portugal). Using micro data we are able to control for

these differences on the firm-level. To assess the divergence in aggregate financing costs more analytically, we estimate the following panel specification:

$$\Delta R_{ijt} = \sum_{t=2006}^{2013} \beta_t year_t + \sum_{t=2006}^{2013} \delta_t year_t * stressed_j + \sum_{k=1}^K \gamma_k \Delta z_{ikt} + \sum_{l=1}^L \zeta_l \Delta w_{jt} + \varepsilon_{ijt}, \quad (2.3)$$

where $year_t$ denotes a set of year dummies and $year_t * stressed$ a set of interaction terms between these year dummies and the indicator variable $stressed$ which is 1 for stressed countries (Ireland, Italy, Spain and Portugal) and zero otherwise (Austria, Finland, France, Germany). In addition, we include the set of aforementioned $K = 7$ firm-specific control variables z_{ikt} and a set of $L = 2$ country-specific macro control variables w_{jt} to be explained below. The model is specified in first differences in order to account for unobserved firm-specific heterogeneity. The sample is 2006 to 2013 and we use a balanced panel to deal with potential problems regarding the entry and exit of firms. The results are shown in table 2.3.

Column 1 contains the baseline specification using only year dummies and the interaction terms between year dummies and $stressed$, thus quantifying the results observed in figure 2.3. Reported marginal effects correspond to percentage point changes in firms' financing conditions. Until 2010 the sign of the change in refinancing costs was the same for both stressed and non-stressed countries. This, however, changed in the years 2011 and 2012, where the change in refinancing costs has been negative for non-stressed countries ($\beta_{2011} = -0.008$ and $\beta_{2012} = -0.102$), but positive for stressed countries ($\beta_{2011} + \delta_{2011} = 0.163$ and $\beta_{2012} + \delta_{2012} = 0.137$); the differences are significant at the 0.1% level. In 2013, financing costs have decreased in both country groups, although the reduction was smaller in stressed countries ($\beta_{2013} < 0, \beta_{2013} + \delta_{2013} < 0, \delta_{2013} > 0$).

As mentioned above, simply looking at the aggregate refinancing costs in the two country groups neglects potential country- and firm-specific heterogeneities across and within countries, respectively. To account for these differences, we add our previously described set of micro variables and dummies controlling for firm size to the baseline specification. Furthermore, we include the growth rate of gross domestic product and the change in the re-

Table 2.3: Different evolution of financing costs across countries – balanced panel

Variable	1	2
year2008	0.134*** (0.00510)	0.0848*** (0.00578)
stressed*2008	0.115*** (0.00570)	0.0769*** (0.00593)
year2009	-0.322*** (0.00591)	-0.262*** (0.00800)
stressed*2009	-0.306*** (0.00648)	-0.304*** (0.00684)
year2010	-0.180*** (0.00467)	-0.300*** (0.00605)
stressed*2010	-0.245*** (0.00516)	-0.226*** (0.00532)
year2011	-0.00787 (0.00403)	-0.132*** (0.00561)
stressed*2011	0.171*** (0.00445)	0.251*** (0.00529)
year2012	-0.102*** (0.00398)	-0.162*** (0.00484)
stressed*2012	0.239*** (0.00444)	0.313*** (0.00629)
year2013	-0.120*** (0.00382)	-0.183*** (0.00475)
stressed*2013	0.0133** (0.00432)	0.0859*** (0.00532)
micro controls	no	yes
macro controls	no	yes
N	1.380.966	1.327.969
R^2	0.099	0.110
adj. R^2	0.099	0.110

Notes: Dependent variable is the difference of the financing conditions indicator. The set of firm-specific variables (micro controls) is described in the text. Marginal effects reported in all columns with cluster-robust standard errors at the firm level in parentheses. Statistical significance at the 5, 1, 0,1 percent levels denoted by *, **, ***, respectively.

spective country's unemployment rate to account for real economic activity in the respective countries. The results are depicted in column 2.

As can be seen, the results of the baseline specification remain qualitatively unchanged: Until 2010 the sign of the change in refinancing costs was the same for both stressed and

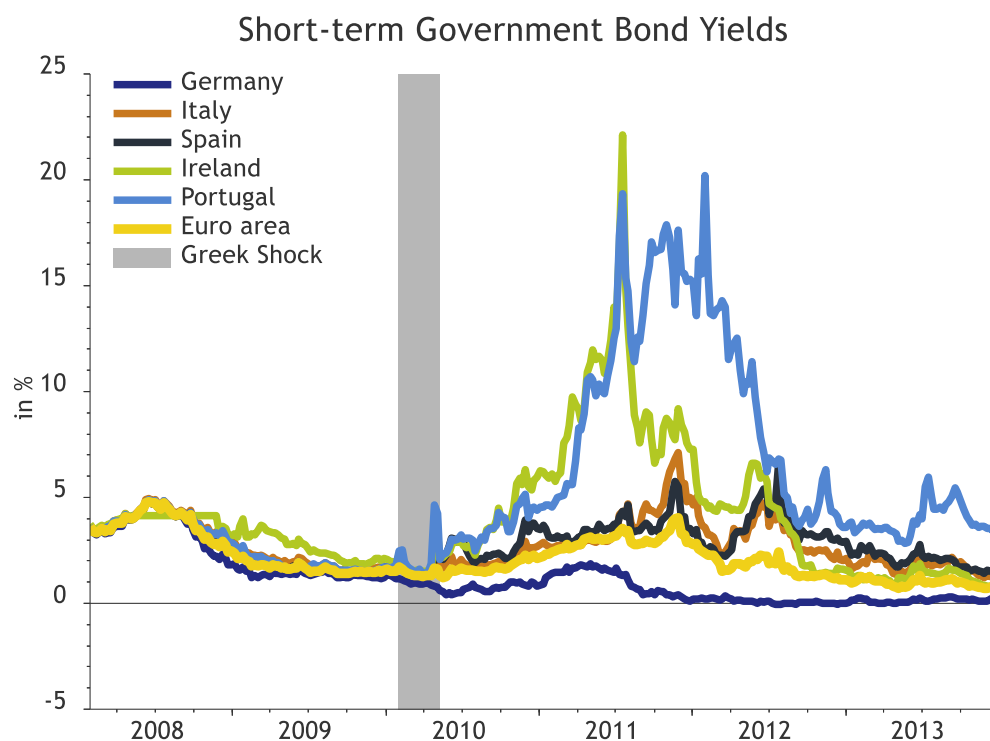
non-stressed countries, while the change in refinancing costs was negative in non-stressed countries, but positive for stressed countries in the years 2011 and 2012. The added control variables exhibit the expected signs – firms face higher financing costs if GDP growth in their respective country is lower and if the unemployment rate in the firms' home country increases. In addition, we find that small and medium firms have higher financing costs, as can be seen in the complete estimation results in table 2.7 in the appendix. However, controlling for micro- and macroeconomic determinants yields quantitatively quite different results, compared to the specification without control variables. For example, financing costs decreased stronger in the non-stressed countries in 2011 and 2012 with the controls. This suggests that the included variables are relevant for the estimation and therefore accounting for heterogeneities across and within countries is important to explain the observed aggregate differences.

2.4 Sovereign stress and firm-level refinancing costs

2.4.1 Sovereign stress in 2011 and 2012

Starting in late 2009 with the onset of the European debt crisis, several Euro area countries experienced years of highly increased sovereign stress, commonly defined as episodes with high risk premiums on sovereign bond yields. Figure 2.4 depicts the yields of short-term government bonds (FTSE 1-3 years) in our set of stressed countries together with the corresponding yields of Germany and the Euro area as a whole. Especially during the years 2011 and 2012 the risk premiums of the stressed countries have been markedly elevated. The shaded area in 2010 marks the beginning of the „Greek shock“, when the public learned about the economic problems in Greece and contagion effects began to affect other (later stressed) countries with a high debt burden. Importantly, before the „Greek shock“ the yields have been almost identical for all countries, strengthening our assumption that this event was in fact exogeneous to other countries' firms.

Figure 2.4: Short-term government bond yields

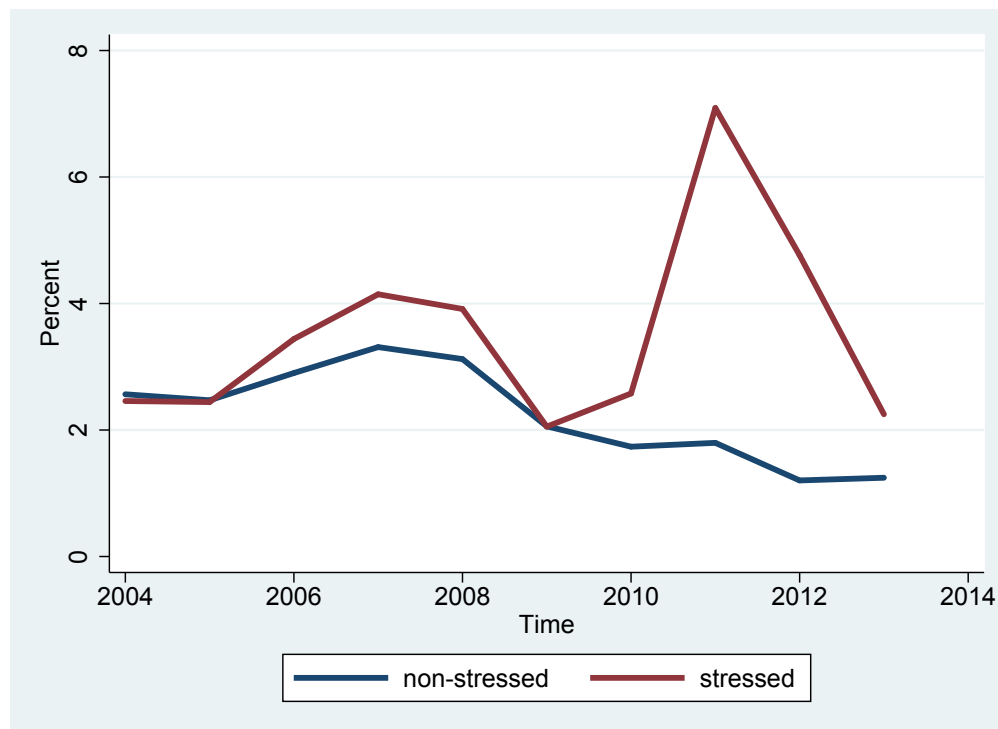


Notes: Depicted are FTSE Global Government Bond Yields, 1-3 Years.

Examining the yields on government bonds in the Euro area countries specifically for the stressed and non-stressed countries, we see in figure 2.5 the sharp bifurcation between both groups. In the first half of the sample until 2009, government bond yields evolved in a parallel manner with only a minimal average premium for the later stressed countries. This, however, changed completely in the second half of the sample. Starting in 2010, the yields for both country groups diverge substantially, reaching a difference of about five percentage points in 2011 and about three percentage points in 2012 in the wake of the European debt crisis. Because of a decline in the yields for the stressed countries, the difference then diminished again in 2013.

This sovereign stress in turn negatively affected the financial system, especially the behavior of banks (Panetta et al. 2011). The resulting impairment of the monetary transmission mechanism was the ground on which the European Central Bank (ECB) decided to intervene in the public and private debt securities markets.

Figure 2.5: Government bond yields in stressed and non-stressed countries



Notes: Stressed countries are Ireland, Italy, Spain and Portugal. Non-stressed countries refers to Austria, Finland, France, Germany and the Netherlands. FTSE Global Government Bond Yield, 1-3 Years. Source: ThomsonReuters Datastream.

2.4.2 Evidence on the link between government bond yields and firms' financing costs

From the perspective of a bank, government bonds are alternative assets for loans to private households and non-financial corporations. Therefore, the return of government bonds and loans to private households and firms should be connected, especially if the bulk of banks' lending to non-financial corporations is directed to domestic firms as is the case for the countries in our sample. According to the expectation hypothesis of the term structure, government bond yields should reflect expected changes in the money market rate such that bank lending rates and government bond yields of similar maturities should exhibit similar dynamics over time. In addition, banks hold government bonds as assets in their balance

sheets and thus are directly affected by changes in the prices of these assets. This is a key mechanism in the model of Bocola (2016) described in the theoretical considerations in section 2.2.⁶ We use the spread of government bond yields against a reference country (Germany) in order to eliminate the common Euro area wide component of government bond yields.

2.5 Banking stress and firm-level refinancing costs

Sovereign stress may not be the sole macroeconomic determinant of firms' financing costs. A potential shortcoming of government bond yield spreads in the European debt crisis is that although they are an important determinant of banking stress, they may not fully capture the distortions in the financial sector. As suggested in the model of Bocola (2016), stress on the financial side is one aspect, however, one also needs to take into account banking stress through the asset side of banks' balance sheets, when real economic fundamentals in stressed countries deteriorate. One variable to measure this dimension is the share of non-performing loans of banks.⁷ If the aggregate share of defaults on corporate loans increases in a country, the banks in the respective country may be forced to demand a premium when granting new loans.⁸ In addition, Noth and Tonzer (2017) compare commonly used measures of bank risk in the literature and show that the share of non-performing assets (with loans being one component of this measure) performs best in explaining failures of banks one year ahead.

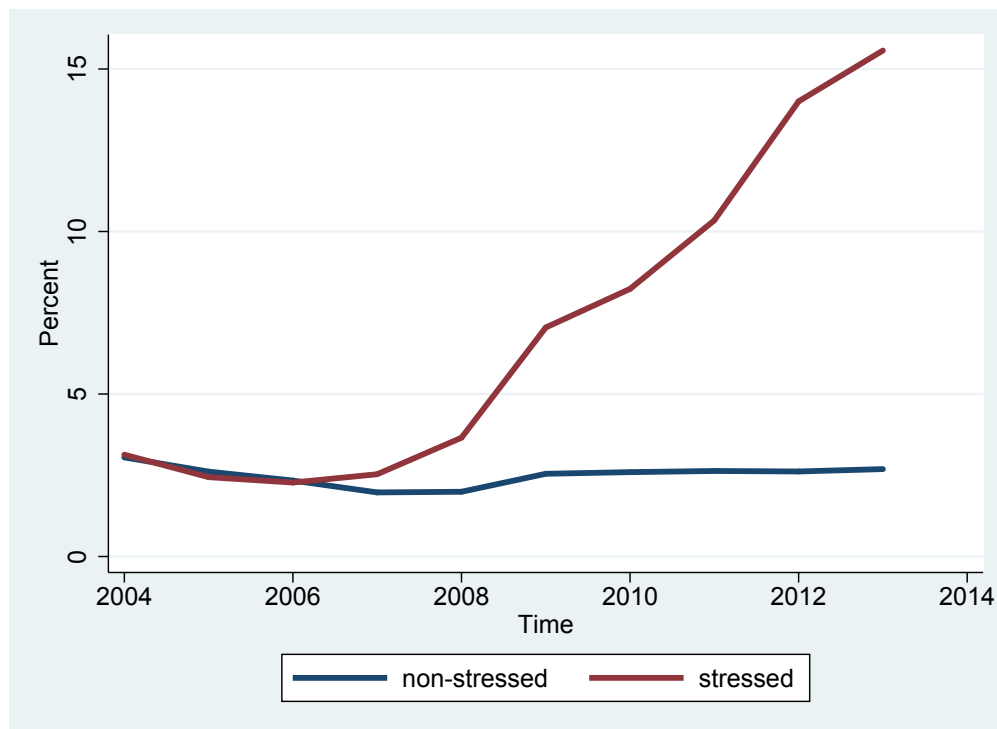
Moreover, non-performing loans are a reasonable measure in the context of our analysis for one important reason. The variable is a real-economic, micro-based measure and as such subject to at most indirect influence of the central bank, unlike the yields on sovereign bonds which as described above are an explicit target of the ECB's unconventional monetary policy actions. Accordingly, this allows analyzing the effects of monetary policy given the

⁶ For further details on the relationship between bank lending rates for firms and government bond yields see Elron, Gruber, Agrawal and Mann (2001), Chatelain and Tiomo (2001) and Chatelain et al. (2003).

⁷ Due to data unavailability we estimate the share of non-performing loans for Finland in 2013 by a univariate autoregressive process.

⁸ See Corsetti et al. (2013) and Zoli (2013) for further considerations on the effects of non-performing loans.

Figure 2.6: Non-performing loans in stressed and non-stressed countries



Notes: Non-performing loans are defined as bank non-performing loans to total gross loans in percent. Source: World Development Indicators (World Bank).

real-economic stress in the banking sector. At the same time, the exogeneity assumption we have to presume in order to infer the causal effect of the macroeconomic variables on firm-level financing conditions is fulfilled, as the effect of one single firm on the country average is inconsequential. Therefore, our empirical set-up allows analyzing the causal effect of the macroeconomic variables on firm-level financing conditions.

Figure 2.6 depicts the share of non-performing loans to the private sector for stressed and non-stressed countries over time. Initially the share is small and almost identical for both country groups with an only marginally higher share in the stressed countries. Moreover, it declines further until 2007. With the Great Recession non-performing loans rise in both country groups until 2009, when the paths for the two country groups diverge: While the share of non-performing loans decreases somewhat in the non-stressed countries in 2010 and increases only slightly thereafter, the respective share in the stressed countries continues to

rise strongly. As a consequence, in 2013 the share of non-performing loans is roughly four times as large in the stressed countries as in the non-stressed group.

2.6 Estimation and Results

In order to explore the impact of government bond yields and non-performing loans on firm-specific financing conditions, we estimate the following panel regression model:

$$\begin{aligned} \Delta R_{ijt} = & \delta \Delta im_t + \beta \Delta \tilde{G}_{jt} + \eta \Delta npl_{jt} + \sum_{k=1}^K \gamma_k \Delta z_{ikt} \\ & + \sum_{k=1}^K \phi_k(z_{ikt} * \Delta im_t) + \sum_{l=1}^L \zeta_l \Delta w_{jt} + \alpha_j + \varepsilon_{ijt}, \end{aligned} \quad (2.4)$$

where Δim_t denotes the change in the money market rate, $\Delta \tilde{G}_{jt}$ the change in the spread of the government bond yield for country j in period t to the corresponding yield for Germany, and Δnpl_{jt} the change in non-performing loans of banks in country j in period t . In addition, z_{ikt} denotes the set of K firm-specific control variables, $z_{ikt} * \Delta im_t$ the interactions between these micro variables and the change in the money market rate, w_{jt} a set of L country-specific macro control variables and α_j a set of country fixed effects.

In the theory outlined in section 2.2 we derived that the monetary transmission mechanism and thus δ should depend on both sovereign and banking stress. Accordingly, and assuming a linear relationship,

$$\delta = \alpha_0 + \lambda \tilde{G}_{jt} + \tau npl_{jt} \quad (2.5)$$

Plugging in the relationship in 2.5 into 2.4 then yields the final specification to be estimated:

$$\begin{aligned} \Delta R_{ijt} = & \theta \Delta im_t + \beta \Delta \tilde{G}_{jt} + \eta \Delta npl_{jt} + \lambda(\Delta im_t * \tilde{G}_{jt}) + \tau(\Delta im_t * npl_{jt}) \\ & + \sum_{k=1}^K \gamma_k \Delta z_{ikt} + \sum_{k=1}^K \phi_k(z_{ikt} * \Delta im_t) + \sum_{l=1}^L \zeta_l \Delta w_{jt} + \alpha_j + \varepsilon_{ijt}, \end{aligned} \quad (2.6)$$

with $\theta = \lambda * \alpha_0$ and $\Delta im_t * \tilde{G}_{jt}$ and $\Delta im_t * npl_{jt}$ the interaction effects between the change in the money market rate and the level of government bond yield spreads and the level of

non-performing loans, respectively. The model is specified in first differences in order to account for unobserved firm-specific heterogeneity and estimated as a pooled cross-section. We assume that \tilde{G} and npl are exogenous, that is uncorrelated with firm-specific shocks ε_{ijt} . In case of \tilde{G} , this seems plausible to us because the rise in government bond yields in stressed Euro area countries occurred in the course of the Greek crisis, as can be seen in figure 2.4. At that time, the perception of vulnerability of Euro area countries with high debt burdens changed. This change in perception was most likely not triggered by firm-specific idiosyncratic shocks in the countries in our sample; remember that we do not include Greek firms. In case of npl , the exogeneity assumption might be a little bit more questionable, but we do control for firm-specific factors like the ratio of debt to total assets which affect the riskiness of individual firms and for factors that are related to aggregate demand (GDP growth and unemployment rate) and therefore the ability of all firms to repay their debt. However, we cannot completely rule out that our estimated coefficients are biased. If \tilde{G} and npl were endogenous, the correlation between them and the error terms would most likely be positive. Consequently, the corresponding coefficients would be biased upwards.

An additional concern may be that, because of the interaction between the two described above, it may be difficult to distinguish between sovereign and banking stress empirically, implying multicollinearity in our regression specification. Inspecting the corresponding graphs for the government bond yield spread (figure 2.5) and non-performing loans (figure 2.6), however, we see that there is no problem of potential multicollinearity, as the two measures employed clearly are not highly correlated and indeed capture the two interrelated but distinct sources of macroeconomic stress.

The interaction effects allow to analyze the effect of monetary policy on firm's financing conditions conditional on the level of sovereign and banking stress. If our exogeneity assumption for \tilde{G} and npl was not fulfilled, the corresponding estimated coefficients would also be biased upwards. However, this would work against our hypotheses for the interaction effects. If we still find significant negative interaction effects, this would actually support our hypothesis.

The sample is 2005 to 2013 and we again use a balanced panel to deal with potential problems regarding the entry and exit of firms. Standard errors are clustered on the firm level.⁹ The results of the estimations are shown in table 2.4.¹⁰

Column 1 presents a naive specification with neither sovereign nor banking stress, but with macro controls, country fixed effects, the full set of firm variables, and the full set of interaction terms between the firm variables and the change in the money market rate. The change in the money market rate is estimated to have a positive effect on firms' financing conditions. The coefficient is highly significant and economically large. The marginal effect of the change in the money market rate (taking into account the interaction terms with the set of micro variables) is estimated to be 0.33. Accordingly, the results imply that on average one third of a change in the money market rate is passed on to firms.

To incorporate sovereign stress into the analysis we then add the government bond yield spread in column 2. While the the estimate for the money market rate is basically unchanged, the coefficient on the spread $\Delta\tilde{G}$ is highly significant and has the expected sign – a rise in sovereign stress increases the financing conditions of firms in the respective country, while controlling for the firm-specific and macroeconomic variables described above.

As suggested by the model of Bocola (2016) in section 2.2 and the considerations in section 2.5, sovereign stress may not only have a direct effect on firms' financing conditions but in addition an indirect effect through the balance sheets of banks, conjecturing an important role for banking stress in the monetary transmission mechanism and firms' financing conditions.

⁹ Since we observe firm-level data in different countries, different firms in the same country and year may be correlated due to a shared macroeconomic background. Accordingly, there could be cross-sectional dependence for which standard errors need to be adjusted. The natural solution to this potential problem is to additionally cluster the standard errors on the time dimension (two-way clustering). However, Petersen (2009) shows that if the number of clusters in one dimension is very small (in his example 10 years and 10k firms), the estimated standard errors are basically the same whether the researcher clusters just on the larger dimension (the firm level in our case) or on both. We only have 9 clusters in the time dimension (10 years and regression specification in first differences) and more than 200k firms, so the result in Petersen (2009) applies to our case. We were even unable to compute the two-way clustering solution, as Stata could not carry out the command. As a result, we cluster our standard errors on the firm level. The critical assumption in this is that there is no correlation between firms of the same country for different years. We argue that this is highly plausible, since we are dealing with annual data in first differences in our estimations.

¹⁰ We provide the full estimation results including the micro variables employed in table 2.8 in the appendix.

Table 2.4: Results of panel estimation – balanced panel

Dependent variable is the difference of financing costs

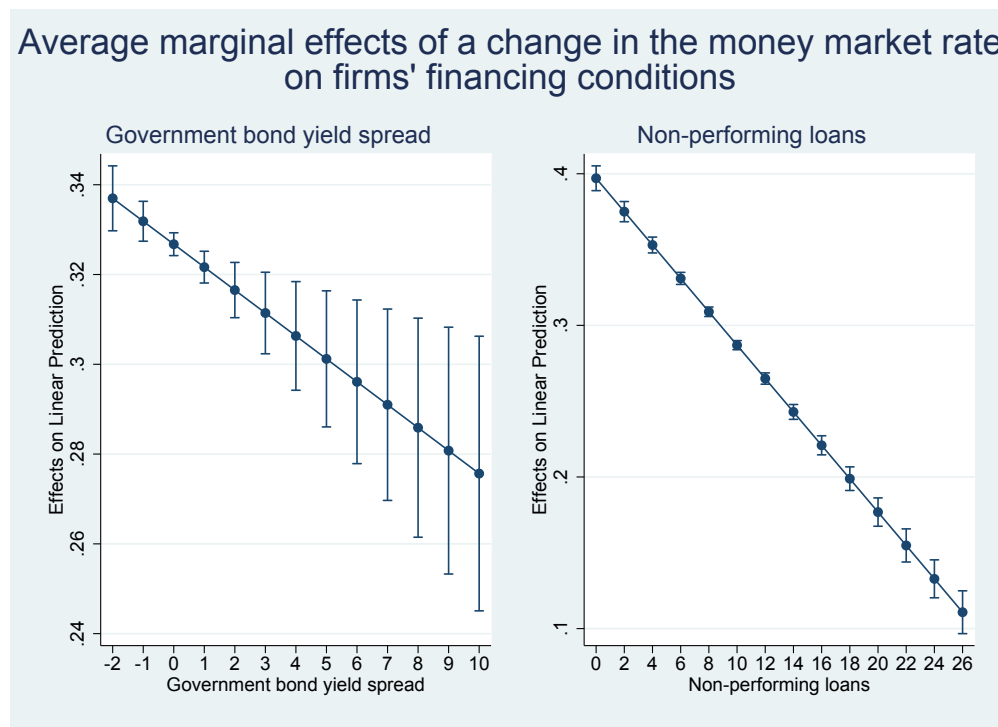
Variable	1	2	3	4
Δim	0.669*** (0.246)	0.666*** (0.246)	0.658*** (0.246)	0.707*** (0.248)
$\Delta \tilde{G}$		0.0228*** (0.0007)	0.0253*** (0.0007)	0.0307*** (0.0009)
Δnpl			0.0342*** (0.0011)	0.0209*** (0.0013)
$\tilde{G} * \Delta im$				-0.0051*** (0.0016)
$npl * \Delta im$				-0.0110*** (0.0004)
cons				-0.0791*** (0.0067)
micro controls	yes	yes	yes	yes
micro interaction terms	yes	yes	yes	yes
macro controls	yes	yes	yes	yes
country FE	yes	yes	yes	yes
N	2.000.041	2.000.041	2.000.032	2.000.032
R^2	0.060	0.060	0.060	0.058
adj. R^2	0.060	0.060	0.060	0.058

Notes: Dependent variable is the difference of the financing conditions indicator. The set of firm-specific variables (micro controls) is described in the text. Marginal effects reported in all columns with cluster-robust standard errors at the firm level in parentheses. Statistical significance at the 5, 1, 0,1 percent levels denoted by *, **, ***, respectively.

We take stress in the banking sector into account by adding the share of non-performing loans to the specification. As can be seen in column 3 of table 2.4, the change in the share of non-performing loans is estimated to significantly increase firms' financing costs. Note that, while the coefficient estimates are relatively small, the overall effect is economically relevant: The share of non-performing loans in stressed countries increased by roughly 13 percentage points between 2007 and 2013 (see figure 2.6), implying an increase in firms' financing costs by 0.44 percentage points. The remaining coefficients are qualitatively unchanged compared to the previous results.

In the last column we introduce interaction terms for the change in the money market rate

Figure 2.7: Estimated interaction effects



Notes: Depicted are the average marginal effects of a change in the money market rate on firms' financing conditions given the level of government bond yield spread and non-performing loans, respectively, with 95% confidence intervals. Results are based on the specification in column 4 of table 2.4.

with the levels of both the spread and non-performing loans, respectively, to shed light on the question whether the level of existing stress – for both sovereigns and in the banking sector – impairs the monetary transmission mechanism in the Euro area. Our results support this hypothesis, as the coefficients of both interaction terms are estimated to be significantly negative. Accordingly, the level of both sovereign and banking stress reduces the effect of a change in the money market rate on firms' financing conditions, impairing the monetary transmission mechanism.

Although the size of the coefficients on the interaction terms is small, the reducing effects are notable, especially for the share of non-performing loans. Figure 2.7 plots the marginal effects of a change in the money market rate for different levels of government bond yield spreads and non-performing loans, respectively. In the absence of interaction terms with the

two sources of stress, the pass-through of a change in the money market rate (marginal effect) was estimated to be 0.33 percentage points. However, taking into account interaction effects changes this result, as the marginal effect hinges on the levels of the government bond yield spread and non-performing loans in the respective country. For the highest observed level in the government bond yield spread in our sample, the pass-through is reduced to around 0.28 percentage points. The reducing effect is much larger in the case of non-performing loans, as the estimates imply that the pass-through becomes very small for higher levels of banking stress. For the highest observed level of non-performing loans in our sample, the pass-through of monetary policy is only about 0.11 percentage points, down from 0.4 percentage points when the share of non-performing loans is zero.

2.7 Conclusions and policy implications

In this paper, we analyze to what extent financing conditions of non-financial corporations in the Euro area depend on country-specific factors, in particular the respective country's government bond yield spread versus Germany (sovereign stress) and the share of non-performing loans (banking stress), and how they affect the monetary transmission mechanism. Our main results are that both the government bond yield spread and the share of non-performing loans significantly increase firms' financing costs. This cannot be explained by firm-specific characteristics like leverage or profitability but does also hold true when controlling for firm characteristics. Moreover, both sources of stress have a significantly negative effect on the monetary transmission mechanism. The higher the stress levels the smaller is the reaction of firms' financing conditions to changes in the monetary policy rate. The mitigating effect is particularly pronounced for the share of non-performing loans and the associated banking stress.

This result is important for the effectiveness of monetary policy. Asset purchase programs that target at lowering government bond yields may only have a limited impact on firms' financing conditions if banking stress is the main reason for high financing costs. For monetary policy to be fully effective – be it conventional interest rate policy or unconventional

asset purchase programs – it is necessary to reduce the level of banking stress in all member countries of the Euro area.

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Appendix

Data

Micro-level data

Table 2.5: Firm-level variables used

Variable	Description	Definition
cashflow	cash flow	cash flow/balance sum
fassets	fixed assets	fassets/balance sum
ltbfunds	long-term borrowed funds	ltbfunds/balance sum
stbfunds	short-term borrowed funds	stbfunds/balance sum
ofrentability	own funds rentability	profit/own funds*100
ofratio	own funds ratio	own funds/balance sum*100
roi	return on investment	profit/balance sum*100

Notes: Variables are taken from the „Amadeus“ data set of Bureau van Dijk.

Table 2.6: Descriptive statistics of micro-level variables

Variable	mean	min	max	sd	p25	median	p75
cashflow	5.9	-71.2	50	7.0	2.0	4.7	8.9
fassets	35.5	0	99.4	27.9	11.3	29.2	55.3
ltbfunds	19.9	0	100	19.3	4.7	14.2	29.6
stbfunds	48.0	0	100	24.2	29.1	48.2	67.0
refinancing costs	2.4	0.0	11.6	1.7	1.1	2.1	3.3
ofrentability	6.4	-259.3	250	27.8	0.2	5.3	15.3
ofratio	32.1	-94.9	100	22.0	14.3	28.3	46.6
roi	2.2	-101.3	44.8	6.1	0.1	1.2	4.1

Notes: All statistics in percent, i.e shares (see table 2.5) are multiplied by a factor of 100. p25 and p75 denote the 25% and 75% percentile, respectively.

Macro-level data

Money market rate: The money market rate is the Euro Overnight Index Average (EONIA) published by the ECB.

Bank lending rate: Loans to non-financial corporates rate, new business, up to one year, up to one million euro, ECB MFI Statistics (downloaded via ThomsonReuters Datastream, code: [JJ]IRUU1B, where [JJ] denotes the country code).

Government bond yields: FTSE Global Government Bond Yield, 1-3 Years, Euro (downloaded via ThomsonReuters Datastream, code: RG[JJ]1T3(RY), where [JJ] denotes the country code).

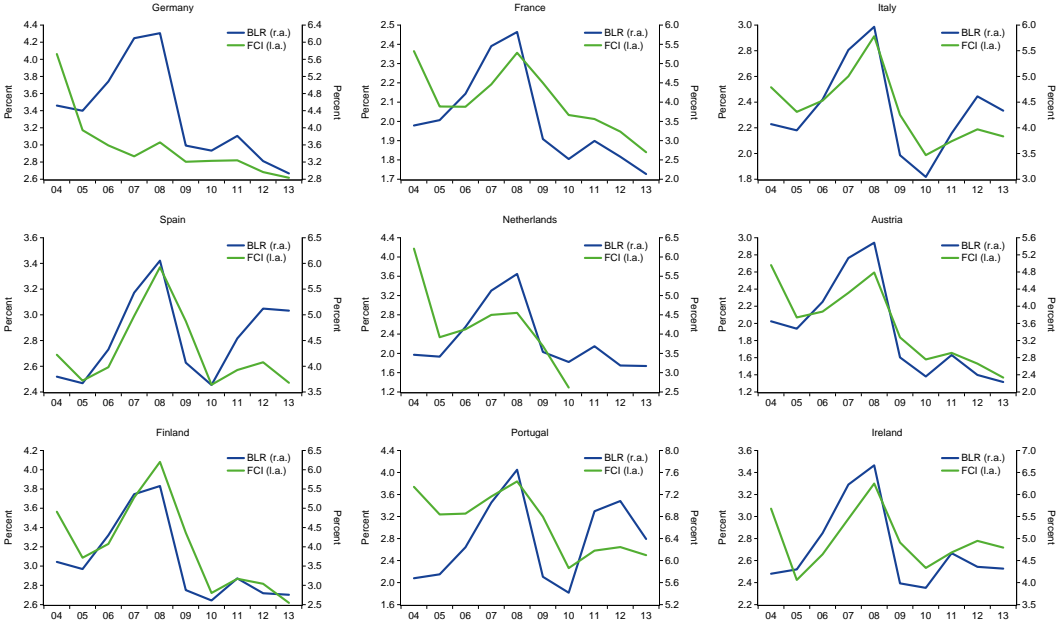
Non-performing loans: Bank non-performing loans to total gross loans in percent from World Development Indicators, published by the World Bank.

Gross domestic product: Yearly growth rate of real gross domestic output, chain linked volumes, published by Eurostat.

Unemployment rate: Unemployment rate, annual average, published by Eurostat.

Additional graphs and tables

Figure 2.8: Financing conditions indicator and aggregate bank lending rate



Notes: Bank lending rate denotes the short-term bank lending rate as published by the ECB (left scale) and the financing conditions indicator constructed from our individual firm data (right scale).

Sovereign Stress, Banking Stress, and the Monetary Transmission Mechanism in the Euro Area

Table 2.7: Results of year dummy regressions complete – balanced panel

Dependent variable is the difference of financing costs

Variable	1	2
year2008	0.134*** (0.00510)	0.0848*** (0.00578)
year2009	-0.322*** (0.00591)	-0.262*** (0.00800)
year2010	-0.180*** (0.00467)	-0.300*** (0.00605)
year2011	-0.00787 (0.00403)	-0.132*** (0.00561)
year2012	-0.102*** (0.00398)	-0.162*** (0.00484)
year2013	-0.120*** (0.00382)	-0.183*** (0.00475)
stressed*2008	0.115*** (0.00570)	0.0769*** (0.00593)
stressed*2009	-0.306*** (0.00648)	-0.304*** (0.00684)
stressed*2010	-0.245*** (0.00516)	-0.226*** (0.00532)
stressed*2011	0.171*** (0.00445)	0.251*** (0.00529)
stressed*2012	0.239*** (0.00444)	0.313*** (0.00629)
stressed*2013	0.0133** (0.00432)	0.0859*** (0.00532)
small		0.0163*** (0.00316)
medium		0.0537*** (0.00303)
Δur		0.0234*** (0.000699)
gdp growth		0.0402*** (0.00129)
$\Delta cashflow/bs$		1.429*** (0.0645)
$\Delta fassets/bs$		0.480*** (0.0158)
$\Delta ltb funds/bs$		-0.459 (0.271)
$\Delta stb funds/bs$		-1.033*** (0.271)
$\Delta ofrentability$		-0.000336*** (0.0000363)
$\Delta ofratio$		-0.00900*** (0.00271)
Δroi		-0.0175*** (0.000667)
N	1.380.966	1.327.969
R^2	0.099	0.110
adj. R^2	0.099	0.110

Notes: Dependent variable is the difference of the financing conditions indicator. The set of firm-specific variables (micro controls) is described in the text. Marginal effects reported in all columns with cluster-robust standard errors at the firm level in parentheses. Statistical significance at the 5, 1, 0,1 percent levels denoted by *, **, ***, respectively.

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Table 2.8: Results of panel estimation complete – balanced panel

Variable	1	2	3	4
Δim	0.669*** (0.246)	0.666*** (0.246)	0.658*** (0.246)	0.707*** (0.248)
small	0.0928*** (0.00327)	0.0928*** (0.00327)	0.0917*** (0.00327)	0.105*** (0.00332)
medium	0.0306*** (0.00317)	0.0303*** (0.00316)	0.0292*** (0.00317)	0.0427*** (0.00322)
Δur	0.0672*** (0.000877)	0.0654*** (0.000880)	0.0647*** (0.000884)	0.0791*** (0.00126)
gdp growth	-0.0458*** (0.000579)	-0.0468*** (0.000584)	-0.0358*** (0.000654)	-0.0323*** (0.000680)
$\Delta cashflow/bs$	2.175*** (0.0608)	2.180*** (0.0608)	2.161*** (0.0608)	2.146*** (0.0608)
$\Delta fassets/bs$	0.621*** (0.0142)	0.620*** (0.0142)	0.624*** (0.0142)	0.626*** (0.0142)
$\Delta ltb funds/bs$	-0.664*** (0.186)	-0.665*** (0.186)	-0.658*** (0.186)	-0.672*** (0.187)
$\Delta stb funds/bs$	-1.294*** (0.186)	-1.295*** (0.186)	-1.289*** (0.186)	-1.300*** (0.187)
$\Delta ofrentability$	-0.000310*** (0.0000364)	-0.000310*** (0.0000364)	-0.000309*** (0.0000364)	-0.000313*** (0.0000364)
$\Delta ofratio$	-0.0110*** (0.00186)	-0.0111*** (0.00186)	-0.0109*** (0.00186)	-0.0111*** (0.00187)
Δroi	-0.0246*** (0.000632)	-0.0245*** (0.000632)	-0.0243*** (0.000632)	-0.0242*** (0.000632)
d^{AT}	-0.0272 (0.0201)	-0.0301 (0.0201)	-0.0464** (0.0201)	0.0258 (0.0211)
d^{ES}	-0.126*** (0.00368)	-0.127*** (0.00368)	-0.164*** (0.00376)	-0.118*** (0.00720)
d^{FI}	-0.114*** (0.00668)	-0.118*** (0.00668)	-0.129*** (0.00668)	-0.0572*** (0.00896)
d^{FR}	-0.0595*** (0.00340)	-0.0585*** (0.00340)	-0.0692*** (0.00342)	-0.00569 (0.00675)
d^{IR}	0.0127 (0.0103)	0.0112 (0.0103)	-0.115*** (0.0109)	-0.0541*** (0.0126)
d^{IT}	-0.0992*** (0.00317)	-0.103*** (0.00318)	-0.134*** (0.00333)	-0.0787*** (0.00677)
d^{PT}	-0.243*** (0.00517)	-0.251*** (0.00519)	-0.280*** (0.00535)	-0.223*** (0.00794)
$cashflow/bs * \Delta im$	-0.328*** (0.0221)	-0.320*** (0.0221)	-0.337*** (0.0220)	-0.412*** (0.0222)
$fassets/bs * \Delta im$	0.148*** (0.00337)	0.149*** (0.00337)	0.147*** (0.00338)	0.144*** (0.00340)
$ltb funds/bs * \Delta im$	-0.250 (0.246)	-0.248 (0.246)	-0.239 (0.246)	-0.208 (0.248)
$stb funds/bs * \Delta im$	-0.386 (0.246)	-0.383 (0.246)	-0.368 (0.246)	-0.334 (0.248)
$ofrentability * \Delta im$	0.0000673* (0.0000346)	0.0000689** (0.0000346)	0.0000760** (0.0000346)	0.0000597* (0.0000348)
$c.ofratio * \Delta im$	-0.00447* (0.00246)	-0.00446* (0.00246)	-0.00446* (0.00246)	-0.00429* (0.00248)
$roi * \Delta im$	0.00268*** (0.000285)	0.00267*** (0.000285)	0.00285*** (0.000285)	0.00307*** (0.000286)
$\Delta \tilde{G}$		0.0228*** (0.000739)	0.0253*** (0.000743)	0.0307*** (0.000868)
Δnpl			0.0342*** (0.00110)	0.0209*** (0.00132)
$\tilde{G} * \Delta im$				-0.00511*** (0.00159)
$npl * \Delta im$				-0.0110*** (0.000421)
cons				-0.0791*** (0.00674)
N	2.000.041	2.000.041	2.000.032	2.000.032
R^2	0.060	0.060	0.060	0.058
adj. R^2	0.060	0.060	0.060	0.058

Notes: Dependent variable is the difference of the financing conditions indicator. The set of firm-specific variables (micro controls) is described in the text. Marginal effects reported in all columns with cluster-robust standard errors at the firm level in parentheses. Statistical significance at the 5, 1, 0,1 percent levels denoted by *, **, ***, respectively. Country abbreviations „at“, „es“, „fi“, „fr“, „ir“, „it“, „pt“ denote Austria, Spain, Finland, France, Ireland, Italy and Portugal. Germany is the reference country.

Sovereign Stress, Banking Stress, and the Monetary Transmission Mechanism in the Euro Area

Table 2.9: Results of fixed effects panel estimation – balanced panel

Dependent variable is the difference of financing costs

Variable	1	2	3	4
Δim	0.586** (0.275)	0.583** (0.274)	0.571** (0.275)	0.618** (0.276)
small	-0.0590*** (0.0111)	-0.0589*** (0.0111)	-0.0594*** (0.0110)	-0.0588*** (0.0110)
medium	-0.0194* (0.0108)	-0.0212* (0.0108)	-0.0214** (0.0108)	-0.0248** (0.0108)
Δur	0.0664*** (0.000881)	0.0646*** (0.000884)	0.0638*** (0.000888)	0.0780*** (0.00127)
gdp growth	-0.0470*** (0.000587)	-0.0480*** (0.000592)	-0.0364*** (0.000664)	-0.0334*** (0.000685)
$\Delta cashflow/bs$	2.207*** (0.0624)	2.213*** (0.0625)	2.191*** (0.0624)	2.177*** (0.0624)
$\Delta fassets/bs$	0.612*** (0.0151)	0.611*** (0.0151)	0.616*** (0.0151)	0.617*** (0.0151)
$\Delta ltbffunds/bs$	-0.699*** (0.186)	-0.700*** (0.186)	-0.694*** (0.186)	-0.707*** (0.186)
$\Delta stbffunds/bs$	-1.297*** (0.186)	-1.299*** (0.186)	-1.293*** (0.186)	-1.304*** (0.186)
$\Delta ofrentability$	-0.000308*** (0.0000367)	-0.000308*** (0.0000367)	-0.000307*** (0.0000367)	-0.000310*** (0.0000367)
$\Delta ofratio$	-0.0103*** (0.00186)	-0.0103*** (0.00186)	-0.0102*** (0.00186)	-0.0103*** (0.00187)
Δroi	-0.0251*** (0.000648)	-0.0251*** (0.000648)	-0.0248*** (0.000647)	-0.0248*** (0.000647)
$cashflow/bs * \Delta im$	-0.284*** (0.0234)	-0.276*** (0.0234)	-0.295*** (0.0234)	-0.373*** (0.0235)
$fassets/bs * \Delta im$	0.135*** (0.00358)	0.135*** (0.00358)	0.133*** (0.00359)	0.131*** (0.00361)
$ltbffunds/bs * \Delta im$	-0.159 (0.275)	-0.157 (0.274)	-0.145 (0.275)	-0.109 (0.276)
$stbffunds/bs * \Delta im$	-0.296 (0.275)	-0.293 (0.274)	-0.273 (0.275)	-0.236 (0.276)
$ofrentability * \Delta im$	0.0000622 (0.0000388)	0.0000638* (0.0000388)	0.0000710* (0.0000388)	0.0000512 (0.0000390)
$c.ofratio * \Delta im$	-0.00366 (0.00275)	-0.00364 (0.00274)	-0.00362 (0.00275)	-0.00341 (0.00276)
$roi * \Delta im$	0.00201*** (0.000309)	0.00200*** (0.000309)	0.00221*** (0.000309)	0.00241*** (0.000310)
$\Delta \tilde{G}$		0.0226*** (0.000741)	0.0252*** (0.000745)	0.0309*** (0.000869)
Δnpl			0.0361*** (0.00111)	0.0230*** (0.00133)
$\tilde{G} * \Delta im$				-0.00618*** (0.00159)
$npl * \Delta im$				-0.0109*** (0.000422)
cons	-0.0198* (0.0103)	-0.0213** (0.0103)	-0.0545*** (0.0103)	-0.0650*** (0.0103)
N	2.000.041	2.000.041	2.000.032	2.000.032
R^2	0.057	0.058	0.058	0.059
adj. R^2	0.057	0.058	0.058	0.059

Notes: Dependent variable is the difference of the financing conditions indicator. The set of firm-specific variables (micro controls) is described in the text. Marginal effects reported in all columns with cluster-robust standard errors at the firm level in parentheses. Statistical significance at the 5, 1, 0,1 percent levels denoted by *, **, ***, respectively.

Chapter 3

Heterogeneous Investment Dynamics in the Euro Area and the Interaction Between the Micro and the Macro Level in a Firm-Level Panel Analysis

Abstract

In this paper I analyze how firm-level investment is affected by interactions between the firm and the aggregate level in the Euro area. Based on the theory of (S, s) models of investment, I derive an interaction effect between firm-level cash flow and GDP growth. Testing this effect in a dynamic error correction panel model, I find that the effect of cash flow on firm investment indeed depends on GDP growth, but only for the subgroup of periphery or stressed countries (Italy, Spain and Portugal) that were hit especially hard in the Great Recession and its aftermath. This interaction created a negative feedback effect which can in part explain the observed differences in the evolution of aggregate investment across Euro area countries.

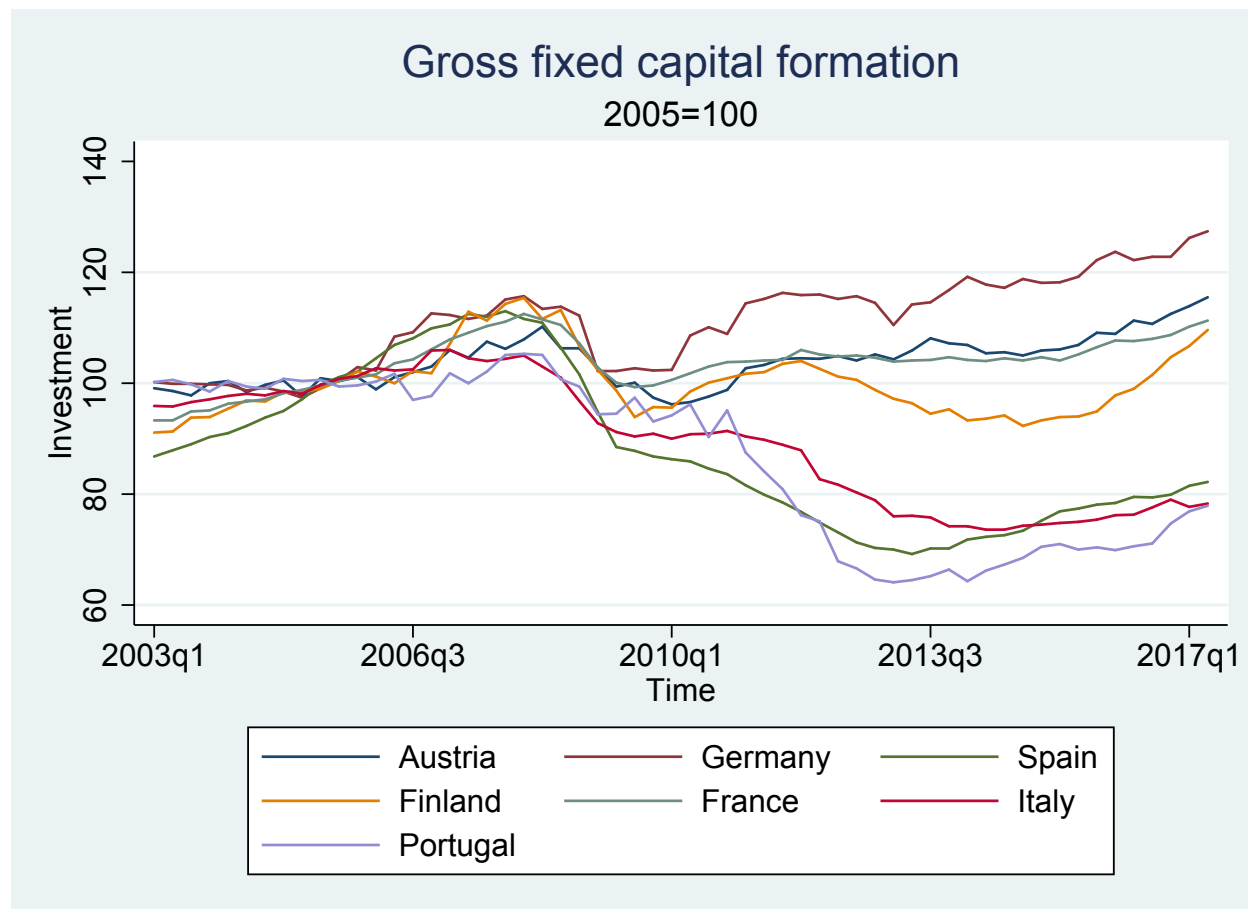
3.1 Introduction

The Great Recession of 2008/09 sent gross domestic products around the world plummeting and left its mark on virtually every statistic: Whether it is total production, trade, stock markets or in interest rates set by central banks, in all facets of economic activity we easily identify the year 2009 just by looking at the graphs. However, while most of the attention in the aftermath of the crisis was on GDP and its heterogeneous recovery across countries, the evolution of its constituting components was not necessarily focused on with the same intensity. One component that deserves more attention is investment. Not only is aggregate investment an important, fast reacting and leading indicator for the stance of the business cycle, but since investment crucially affects the economic development and performance of firms, it also has profound implications for overall economic dynamics and development.

One important aspect of the dynamics of investment are the differences across countries and firms and how the firm and the aggregate level interact to influence these differences. Based on the theory of (S, s) models of investment, in which optimal investment behaviour is characterized by a range of inactivity around the optimal capital stock and trigger points S and s for the firm to act, I examine differences in the evolution of aggregate investment across different Euro area countries. To this end, I combine a large data set on firms' balance sheet information with country-level data to analyze in a dynamic error correction panel model what affects firm-level investment, how these results depend on differences across countries and how macroeconomic shocks influence the process. I show (1) that the effect of cash flow on firm investment depends on the macro level, i.e. there is an interaction effect between firm and aggregate level and (2) that this interaction effect only seems to matter for firms in stressed countries (Italy, Spain and Portugal), but not for firms in non-stressed countries (Austria, Finland, France and Germany). Since GDP growth was lower in these countries, the interaction effect created a negative feedback effect and accelerated the prolonged economic downturn.

To start with the macroeconomic level, Figure 3.1 shows the evolution of aggregate fixed investment (gross fixed capital formation) in different Euro area countries.

Figure 3.1: Evolution of (aggregate) fixed investment across countries



Notes: Depicted is the evolution of aggregate gross fixed capital formation in different European countries, 2005=100.

Several interesting findings emerge. First, the development is very heterogeneous across countries and seems to divide the countries into two distinct sub-groups. In the non-stressed countries (Germany, France, Austria and Finland) investment has recovered somewhat after the Great Recession and has surpassed its level from 2005. In the second sub-group we can see the stressed countries (Italy, Spain and Portugal), whose investment further declined in the European debt crisis of 2012/13. Second, despite the heterogeneity, all investment series share a broad common evolution with investment decreasing during the Great Recession, being flat or further decreasing during the European debt crisis and recovering thereafter.

The common factor is arguably much stronger when considering the countries within the two sub-groups.

To assess these group-specific differences more precisely, figure 3.2 plots the fitted values from separate regressions of investment on the complete set of quarterly time dummies for both stressed and non-stressed countries, together with 2-standard-deviations confidence intervals. In both country groups, investment declined following the Great Recession, however, starting in 2010, investment began to evolve differently. In the stressed countries the decline continued almost until 2013 before stabilizing and slightly increasing afterwards. Still, in the second quarter of 2017 investment was only about 79% of its level in 2005. In the non-stressed countries, however, investment took a small dip in 2012, but rose relatively steady, reaching 116% of its 2005 level at the end of the sample.

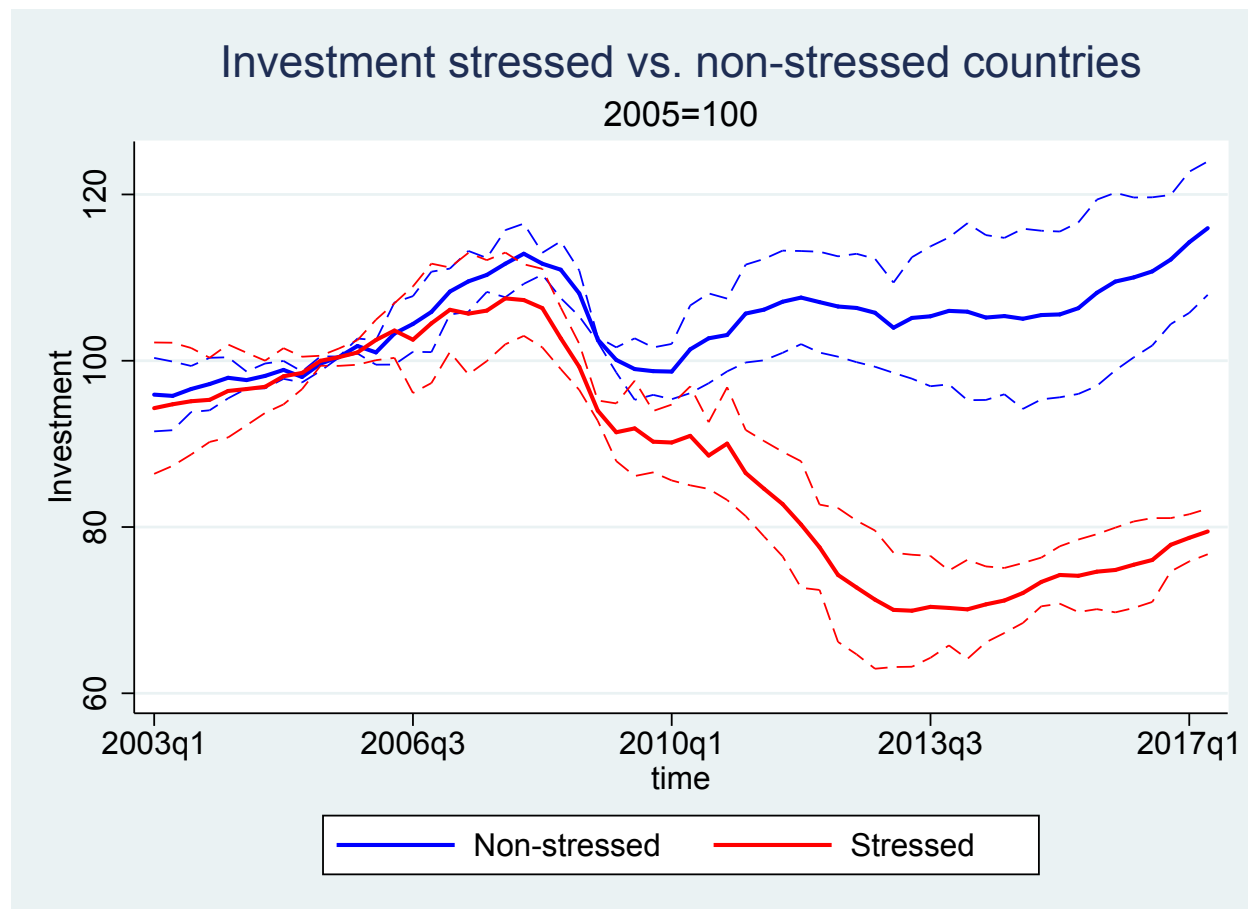
In addition to the graphical analysis above, I estimate an error correction panel model using the Pooled Mean Group (PMG) estimator of Pesaran, Shin & Smith (1999). This estimator allows for group-specific short-run adjustment parameters, while restricting the long-run coefficients to be identical across groups. As indicated in the figures above, investment seems to be heterogeneous across country groups. Therefore, I estimate the model separately for the two sub-groups, thereby allowing for a different long-run equilibrium in each of the two country groups. The selection of variables for the macroeconomic analysis is based on the theoretical investment function from the standard medium-sized DSGE models of Smets & Wouters (2007).¹ The analysis confirms the graphical impression, as I find the long-run equilibria to be significantly different across the two country groups.²

However, while insightful, the observed aggregate investment is already the result of all firms' individual investment decisions. The country-level data can not answer the question which factors influence the investment decision of a specific firm and thus the source of aggregate investment and the observed differences. Therefore, the analysis in this paper focuses on explaining investment at the firm level and how it interacts with macroeconomic conditions.

¹ See the appendix for details on the theoretical derivation and the exact empirical specification.

² See table 3.3 for the estimation results.

Figure 3.2: Evolution of (aggregate) fixed investment across country groups



Notes: Displayed are the fitted values from separate regressions of investment on the complete set of time dummies for both stressed and non-stressed countries, together with 2-standard-deviations confidence intervals.

The analysis in this paper relates to mainly two strands of literature. The first is the so-called (S, s) model of investment, in which firms face non-convex costs of adjusting the capital stock (see, for example, Caballero & Engel (1991) or the overview in Caballero (1999)). As a consequence, optimal investment behaviour is characterized by a range of inactivity around the optimal capital stock and bursts of investment, if the difference between the current and the optimal capital stock becomes too large, reaching the trigger points S and s, respectively. This firm-level investment has important implications for the dynamics of aggregate investment. Caballero et al. (1995) and Caballero & Engel (1999) show that based

on (S, s) models the response of aggregate investment to shocks varies over the business cycle, depending on the synchronization in the distribution of firms. If enough firms are close to their respective trigger points, a shock can cause a sufficient number of firms to invest such that aggregate investment is affected. In this sense, synchronization in the microeconomic distribution of firms results in time-varying elasticities of investment with respect to shocks. The (S, s) model framework is explained in more depth in chapter 3.2. The second strand of literature is the research on the sensitivity of investment to cash flow. Cash flow has been found to be an important determinant of firm-level investment and has been used to assess financial constraints at the firm level (see, for example, Fazzari et al. (1988), Gilchrist & Himmelberg (1995), Gomes (2001) or Almeida & Campello (2007)). In this paper I focus on the effects of cash flow on investment and how macroeconomic conditions impact the effect. The remainder of the paper is organized as follows. Section 3.2 recapitulates the (S, s) theory and the consequences for analyzing firm-level investment. Section 3.3 introduces the firm-level data used in the analysis, followed by the empirical specification in section 3.4. Details on the estimation and the results are then presented in section 3.5. Finally, section 3.6 concludes.

3.2 Theory

3.2.1 Interaction between micro and macro level

One important characteristic of investment at the firm level is its lumpiness, i.e. investment is concentrated in infrequent bursts of activity, which account for the majority of a firm's total investment spending over time. This aspect was put into focus by Doms & Dunne (1998), examining US manufacturing data and since then has been confirmed for example by Gourio & Kashyap (2007) and with data from other countries as well, for example for Germany by Scherer (2019). The widely used quadratic adjustment cost function in contrast can not account for the lumpy nature of investment, as this would incentivise firms to rather gradually adjust their capital stocks.

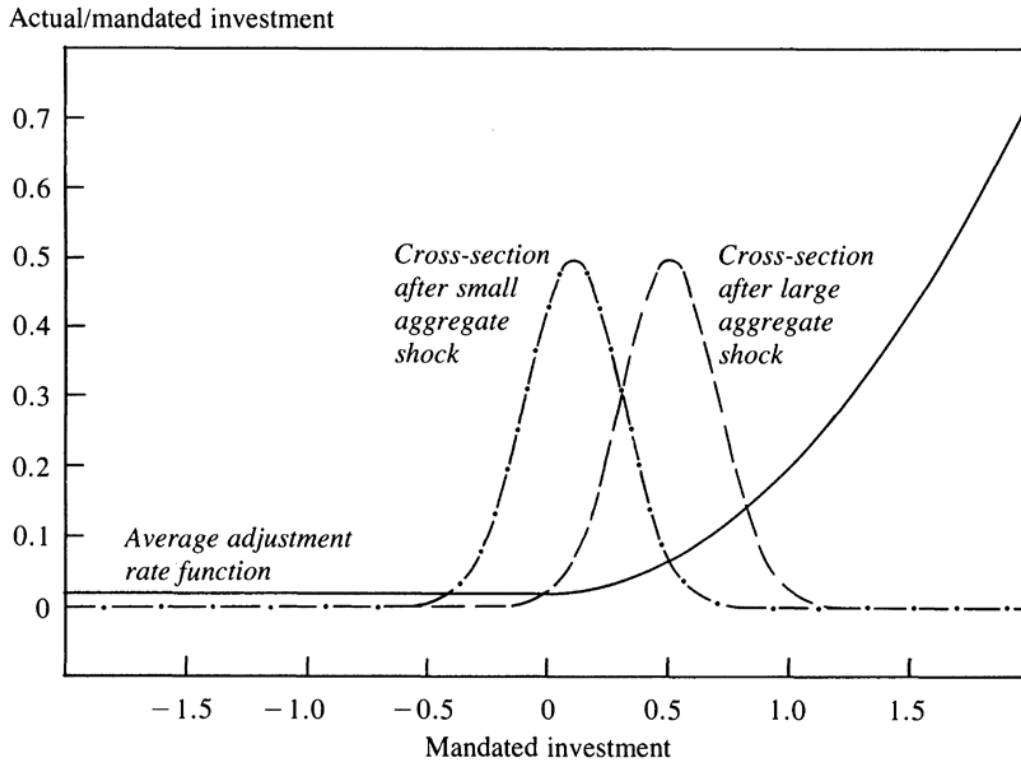
A straightforward way to model the lumpy nature of firm-level investment is to introduce non-convex costs of adjusting the capital stock into the optimization problem of a firm, an approach embedded in the (S, s) models of investment.³ In this model, firms maximize profit by choosing the capital stock. Because of the non-convex costs of adjusting the capital stock, optimal firm investment behaviour can be characterized by the difference between the firms' actual capital stock in the current period and the optimal, frictionless capital stock, i.e. the capital stock the firm would choose if there would be no fixed adjustment costs. Due to the non-convex adjustment costs, investing is profit maximizing only if this difference is large enough. If the difference is too small, not investing is optimal. Therefore, the firm follows a (S, s) -type investment behaviour, characterized by a range of inactivity around the optimal, i.e. frictionless capital stock and trigger points S and s . If the current capital stock is sufficiently below the optimal capital stock, firms will reach the lower trigger point S and invest. Conversely, firms will disinvest if the current capital stock is too large compared to the optimal one, i.e. if they reach the upper trigger point s . In the (S, s) model framework the behaviour of a firm is – given its capital gap – deterministic: It will invest (disinvest) if its capital stock is below (above) the corresponding trigger point, otherwise it will wait.

Caballero & Engel (1999) expand this model by introducing a probabilistic adjustment rule in which large imbalances are more likely to trigger adjustment of the capital stock than small ones, because the fixed cost is random both across firms and time. In addition, they find evidence for an increasing adjustment hazard: expected adjustment of a firm grows more than proportionally with its imbalance. Caballero & Engel (1999) find that this non-linear model performs significantly better in explaining aggregate investment than linear models because of the additional element of pent-up demand.

Figure 3.3 from Caballero et al. (1995) illustrates the mechanisms behind the increasing hazard model. The firm's capital gap is shown on the x axis, labeled „mandated investment“, because it corresponds to the amount of investment the firm would mandate if adjustment costs were removed (and thus the optimal capital stock could be achieved without incurring the fixed cost). The cross-sectional distribution of all firms' gaps can then be depicted as

³ See, for example, Caballero (1999).

Figure 3.3: Non-linear aggregate effects of increasing adjustment hazard



Notes: Interaction of nonlinear adjustment function with aggregate shocks. Source: Caballero et al. (1995), p. 30

a distribution over the space of gaps. The second element is the adjustment hazard which is non-linearly increasing in the capital gaps of firms. A positive shock to the economy will then increase the optimal capital stocks of all firms and thus move the distribution of capital imbalances to the right. This will result in higher firm investment for two reasons. First, the average capital imbalance for a single firm is now higher, resulting in higher adjustments. Second, because the hazard is increasing, after the shock more firms are concentrated in the region in which the adjustment hazard increases more steeply. Thus, firms on average adjust more and more firms adjust. This creates a time-varying elasticity of aggregate investment to aggregate shocks, as the micro non-linearities exacerbate the response of the economy to aggregate shocks. In addition, it illustrates the non-linear effects of aggregate shocks. A

larger shock will move the distribution of imbalances further to the right than a smaller one (see figure 3.3), thus the non-linear effect of the increasing adjustment hazard will be larger. In this sense the pass-through of aggregate shocks from individual firms' reaction to aggregate investment dynamics depends on the distribution of micro-level variables like the distribution of capital imbalances. This includes the dispersion of the distribution. Consider figure 3.3 again. If the distribution of capital imbalances is narrow, then even a relatively small shock can move a sufficient number of firms over the investment threshold to have an impact on aggregate investment. If, however, the distribution is wide, then the same small shock may not move as many firms over the investment threshold, resulting in less change in aggregate investment.

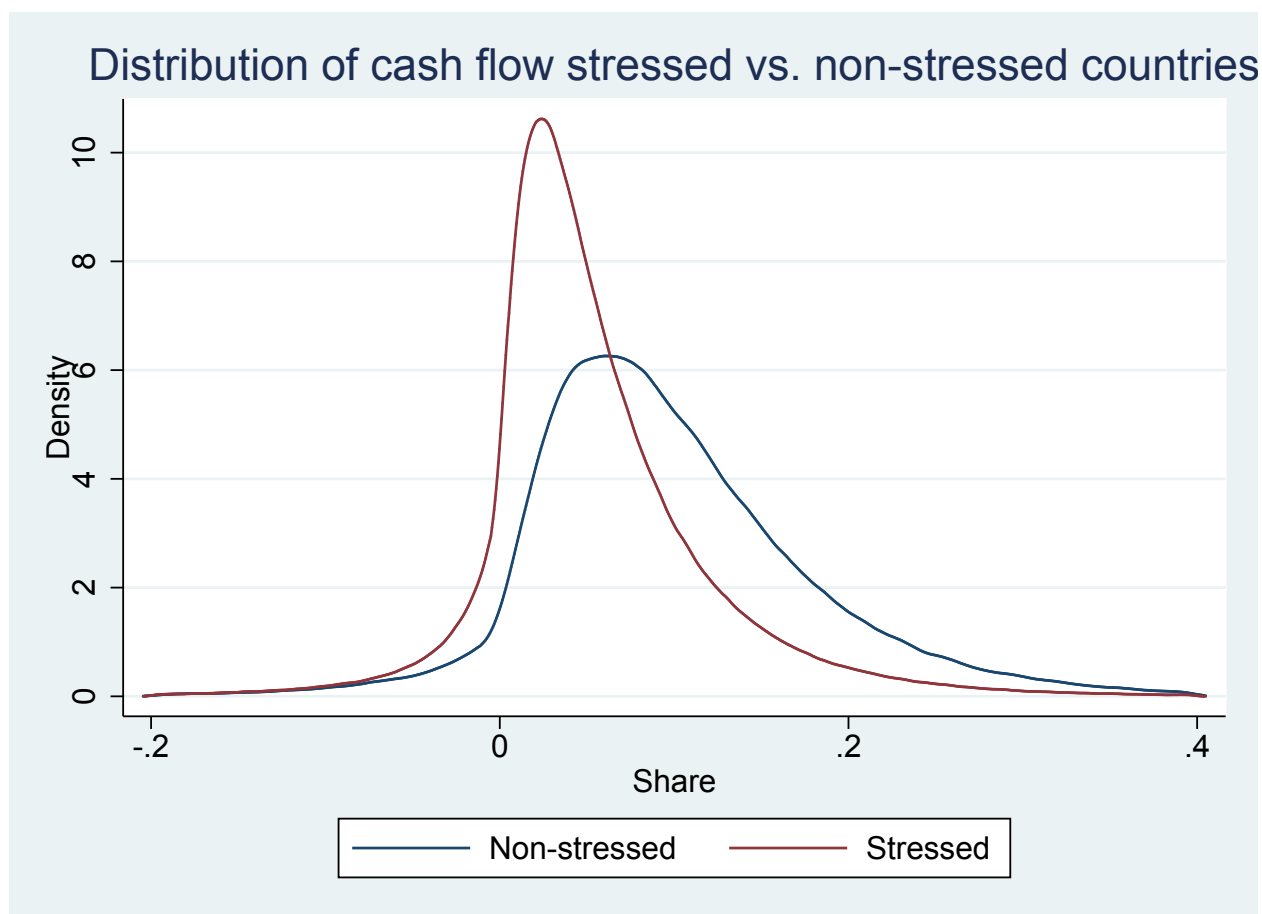
Accordingly, the dynamics of firm investment depend on both the microeconomic fundamentals of the firm and macroeconomic shocks. The fundamentals determine the position of the individual firm within the distribution of firms, but the shocks shift and possibly change the entire distribution. Because of this, macroeconomic factors interact with the firm-level determinants and influence the reaction of investment to the fundamentals itself. Based on the (S, s) model framework and the reasoning above, I propose to capture this interplay between the two sets of determinants by incorporating micro-macro interaction effects in the microeconomic analysis. Estimating a panel model with my firm-level data set to explain corporate investment then allows to test the proposed interaction effect.

3.2.2 Country group differences

As pointed out in the theory section above, the effect of micro-level determinants on firm investment depends on the distribution of these determinants. Therefore, differences in these distributions between subgroups of firms should lead to different effects on firm investment. Following the literature on the investment sensitivity to cash flow, this analysis focuses on cash flow as important determinant of investment. The employed data set on firm balance sheet information allows me to examine the cross-sectional distribution of cash flow and thus potential differences between firms in stressed and non-stressed countries. Figure 3.4 depicts

kernel density estimates of the distribution of cash flow for firms in stressed and non-stressed countries, measured as share of firms' total balance sum.

Figure 3.4: Distribution of cash flow for firms in stressed and non-stressed countries



Notes: Depicted are separate kernel density estimations of the distribution of firm-level cash flow for stressed and non-stressed countries. Kolmogorov-Smirnoff test rejects equality of distributions with a p-value of 0.0000.

Firms in non-stressed countries have on average higher shares of cash flow compared to the firm in stressed countries. In addition, the distribution of cash flow is less right-skewed for the firms in non-stressed countries, resulting in more distributional mass in higher shares of cash flow. In contrast, the cash flow shares of firms in stressed countries are more concentrated at lower values. Testing the two distributions with a Kolmogorov-Smirnoff test confirms the significant differences between them. Therefore, the firm-level estimations not only have to

consider the interaction effects between the micro and the macro level, but also need to be done separately by country group.

3.3 Firm-level data

The firm-level data employed in the analysis are yearly balance sheet data on Euro area firms from the Amadeus data base provided by Bureau van Dijk. The data set has the advantage of containing a large number of firms in different countries and providing comparable financial data. As such, firm coverage is sufficient to analyze a single country as in Egger, Erhardt & Lassmann (2015), but also allows comparison across countries as in Holtemöller & Scherer (2018).

Focusing on non-financial corporations, I exclude financial corporations (NACE classification 6400 to 6700). The sample spans the time from 2004 to 2013 and comprises the seven Euro area member countries Austria, Finland, France, Germany, Italy, Spain and Portugal. Belgium, Greece, Luxembourg and the Netherlands drop out due to insufficient numbers of observations.

To account for unrealistically high observations and outliers, observations are dropped from the sample if current assets, fixed assets, long-term borrowed funds or short-term borrowed funds as a ratio of total balance sum are negative or exceed 1. Afterwards, only firms with observations for the entire sample period are kept to achieve a balanced panel.

Based on this balance sheet data, investment at the firm level is defined as

$$invest_{ijt} = \Delta fixed\ assets_{ijt} + depreciations_{ijt}, \quad j = 1, \dots, J, \quad (3.1)$$

that is as the first difference of the respective firm i 's fixed assets in the current period t and country j , adjusted for depreciations because the latter are added to investment.

Besides cash flow, I control for firms' financing costs as an important determinant of investment. Financing costs at the firm level are measured by interest payments divided by the average of liabilities in the current and previous period.⁴ As a consequence, this variable

⁴ This follows the approach in Holtemöller & Scherer (2018). See this reference for more details.

does not measure marginal financing costs but average financing or capital costs. Table 3.4 in the appendix contains descriptive statistics on the three main variables.

3.4 Empirical specification

While aggregate data presents a summary or average determinants of investment, ultimately, investment decisions are made at the firm level and are subject to the specific financial and economic situation of the corresponding firm. To get to the core of what drives investment and how important financing conditions are, the analysis has to take this firm-specific environment into account. This firm-level heterogeneity is partly washed out in the process of aggregation and thus contained valuable information is ignored, especially when considering the amount of aggregation involved going from the firm to the country level. At the same time, aggregate data provides relevant information for a firm-level analysis, as for example aggregate investment and the gross domestic product are informative about the level of aggregate demand and overall economic activity. This macroeconomic information can easily be included in the firm-level analysis, which therefore can contain „the best of both levels“. The empirical specification employed in this paper is based on the reduced form error correction model (ECM) of Bond, Elston, Mairesse & Mulkay (2003), which is based on the investment optimization problem of a firm facing capital adjustment costs and has been employed in various analyses of firm-level investment behaviour such as Bloom et al. (2007), Guariglia (2008), and, more recently, Mulier et al. (2016).

In this framework, the actual capital stock chosen by the firm under costly adjustment K and the frictionless capital stock the firm would choose without adjustment costs K^* are modelled to have the same long-run growth rate, because the difference between the two is bounded, as the firm will adjust the actual capital stock if the deviation from the frictionless one becomes too large. Accordingly, the logarithms of both are cointegrated, and thus,

$$\log K_{it} = \log K_{it}^* + e_{it} \tag{3.2}$$

The ECM framework therefore represents the underlying idea incorporated in the (S, s) models described in section 3.2 regarding the actual capital stock and its dynamics with respect to the frictionless capital stock. This frictionless capital stock in turn is specified as

$$\log K_{it}^* = \log Y_{it} + A_i^* + B_t^*, \quad (3.3)$$

with Y_{it} the real sales of firm i at time t and A_i^* and B_t^* firm- and time-fixed effects, respectively. In addition, it is assumed that $\Delta \log K_{it} = \frac{I_{it}}{K_{it-1}} - \delta_i$, where I_{it} denotes gross investment and δ_i the depreciation rate. Reformulating equation 3.2 as error correction specification, using equation 3.3 and the assumption above then yields

$$\frac{I_{it}}{K_{it-1}} = \beta_1 \Delta \log Y_{it} + \beta_1 (\log Y_{it-1} - \log K_{it-1}) + A_i + B_t + \delta_i + e_{it} \quad (3.4)$$

Mulier et al. (2016) extends this framework by adding last period investment and cash flow to the explanatory variables. Because of its lumpy nature, investment at the firm level is serially correlated; accordingly last period investment is included to account for this dynamic characteristic. Cash flow (CF), on the other hand, has been shown to be an important determinant of firm investment and is commonly included in empirical analyses.

In addition to cash flow, I also include firms' financing costs (R) as a likely influence investment. Since my data set contains not only listed firms, but also to a large extent unlisted small and medium-sized firms, I can not include Tobin's q , which is often included in empirical analyses of investment decisions at the firm level. Furthermore, my data set comprises different countries. Since firms in the individual countries may be affected by macro-level dynamics in their respective home countries, I also add country-year fixed effects to the regression, thereby accounting for anything that may influence firm-level investment outside firm-level determinants.

With these choices the empirical specification is as follows:

$$\begin{aligned} \frac{I_{ijt}}{K_{ijt-1}} &= \beta_0 + \beta_1 \frac{I_{ijt-1}}{K_{ijt-2}} + \beta_2 \Delta \log Y_{ijt} + \beta_3 (\log Y_{ijt-1} - \log K_{ijt-1}) \\ &+ \beta_4 \frac{CF_{ijt}}{K_{ijt-1}} + \beta_5 R_{ijt} + A_{jt} + e_{ijt} \end{aligned} \quad (3.5)$$

However, based on the theory in section 3.2, the effect of cash flow on investment, β_4 , should depend on macroeconomic shocks. Specifically, I consider the year-on-year growth rate of GDP in t-1 to allow the effects of the shock to be incorporated in firms' investment decisions. For the purpose of the estimation I approximate this dependency by a linear equation, $\beta_4 = \alpha_0 + \alpha_1 GDP_{jt-1}$, yielding the final specification with an interaction term between cash flow and last period GDP growth:

$$\begin{aligned} \frac{I_{ijt}}{K_{ijt-1}} = & \beta_0 + \beta_1 \frac{I_{ijt-1}}{K_{ijt-2}} + \beta_2 \Delta \log Y_{ijt} + \beta_3 (\log Y_{ijt-1} - \log K_{ijt-1}) \\ & + \alpha_0 \frac{CF_{ijt}}{K_{ijt-1}} + \alpha_1 \frac{CF_{ijt}}{K_{ijt-1}} \times GDP_{jt-1} + \beta_4 R_{ijt} + A_{jt} + e_{ijt} \end{aligned} \quad (3.6)$$

3.5 Estimation and results

The dynamic specification in equation 3.6 is estimated using two-step difference GMM with Windmeijer-corrected cluster-robust standard errors and first-difference transformation. These dynamic panel GMM estimators have to be applied with special care, as their complex theory and the substantial number of options with their profound implications the researcher has to decide upon can make the results highly sensitive to the chosen model specifications. To address this issue, I opt for the most conservative choices in all model specifications.

First, as pointed out in Roodman (2009), special consideration has to be given to the number of internal instruments generated in the estimation. Ordinarily, the GMM estimators use every admissible instrument that can be generated internally with the available data, i.e. all lags of all instrumented variables. However, too many internal instruments can severely bias the results. Roodman (2009) shows that the empirical results in several top published papers brake down when the number of instruments is reduced. To make matters worse, instrument proliferation also weakens the Hansen J-statistic, which is used to test for the validity of the set of generated instruments. Therefore, an excessively high instrument count not only leads to biased results, but at the same time also diminishes the ability of tests to detect this misspecification. Roodman (2009) proposes two ways to contain the number of instruments and thus check the robustness of the results with respect to this specific issue. The first

possibility is to limit the lag length of instruments used in the estimation. The second possibility is to collapse the instrument matrix, which works as follows. Each admissible instrumenting lag of an endogenous or predetermined variable can be used as an instrument for the original variable in the corresponding period. Ordinarily, each element of this set of instruments enters the instrument matrix as distinct column, thus giving rise to the problem of instrument proliferation: Without restrictions a separate column is created for every time period and every lag for every variable. As a consequence, the number of instruments is quadratic in T . The columns of the resulting instrument matrix each contain only one non-zero element (the instrumenting lag for the specific time period). Collapsing the matrix (i.e. eliminating the leading zeros in rows with non-zero entries) compresses the information of a specific instrumenting lag into a single moment condition for the sum of all periods, rather than the sum of period-specific moment conditions, thereby reducing the number of instruments. Comparing both possibilities to limit instrument proliferation, Roodman (2009) in simulations finds collapsing to be superior to limiting lag lengths. In addition, when applied to my estimations, collapsing resulted in a stricter reduction in generated instruments. Therefore, I estimate all regressions collapsing the instrument matrix.

Second, I treat all variables as endogenous, as some endogeneity through reverse causality between a firm's investment and its cash flow or financing costs can not be ruled out.

Third, I include a full set of country-year fixed effects to soak up every effect from the macro level in my regressions and isolate the effect of the interaction term.

Lastly, I report the exact instrument count and p-values from tests on serial correlation in every specification. Table 3.1 presents the results of the estimation.

Column 1 contains the result from the baseline model without interaction effects. The error correction term $(y - k)_{i,t-1}$ has the expected positive sign and is highly significant. Accordingly, firms' investment increases with the size of the existing capital gap such that the gap is reduced. A strong and significantly positive effect can also be seen for the growth of the frictionless capital stock, proxied by the growth in turnover, so firms' investment increases as they grow in size. These two variables lie at the core of the error correction model introduced above and the results are in line with expectations. On the other hand the estimation suggests

Table 3.1: Results of dynamic panel estimation

Dependent variable is the difference of financing costs

Variable	1	2	3	4	5
			all	non-stressed	stressed
I_{it-1}/K_{it-2}	-0.0000103 (0.0000523)	-0.0000164 (0.0000519)	0.00000644 (0.0000648)	0.000608 (0.000837)	0.0000151 (0.0000725)
$(y - k)_{i,t-1}$	2.678*** (0.665)	2.272*** (0.588)	2.695*** (0.580)	1.268*** (0.260)	2.778*** (0.611)
Δy_{it}	2.999*** (0.949)	2.496*** (0.870)	3.189*** (0.741)	2.118*** (0.574)	3.273*** (0.765)
CF_{it}/K_{it-1}	0.122 (0.141)	0.144 (0.159)	0.0121 (0.0631)	0.112 (0.105)	-0.00445 (0.0717)
R_{it}		0.0316 (0.0489)	0.0681 (0.0522)	0.115*** (0.0319)	0.0744 (0.0565)
$CF_{it}/K_{it-1} \times GDP_{t-1}$			0.0184 (0.0167)	-0.0112 (0.0124)	0.0445*** (0.0172)
country x year FE	yes	yes	yes	yes	yes
N	1493484	1493484	1493484	199681	1293803
ar1p	0.121	0.121	0.121	0.243	0.124
no. of instruments	77	85	91	70	63
Sargan-Hansen p-value	0.230	0.086	0.171	0.016	0.478

Notes: Dependent variable is the difference of the financing conditions indicator. Marginal effects reported in all columns with cluster-robust standard errors at the firm level in parentheses. Statistical significance at the 5, 1, 0,1 percent levels denoted by *, **, ***, respectively.

no significant effect of the lagged dependent variable, I_{it-1}/K_{it-2} . As outlined in section 3.2, empirical research showed the lumpy nature of firm-level investment, which would indicate a negative effect of the last period investment. Moreover, examining the results in column 1 more closely, this non-result is not due to a high standard error of the estimate, but rather a very small estimate of the coefficient itself. It may be the case that the error correction setup of the model might actually already capture the effects of the lagged dependent variable. In their analysis, Mulier et al. (2016) do not find consistently significant results for this variable for all countries in their sample either. Finally, I find no significant effect of cash flow on firms' investment. This is surprising, as cash flow is the most important determinant of firm-level investment throughout both theoretical and empirical research. Adding the financing costs to the specification in column 2 does not change the baseline results too much, the only

difference is a slightly lower estimate for the error correction term and the growth in turnover. Moreover, the estimate of the coefficient itself is insignificant. Column 3 then introduces the interaction effect between firm-level cash flow and aggregate GDP growth. The coefficient estimate is positive, but insignificant. However, as suggested in section 3.2, the interaction effect should depend on separating the subgroups of stressed and non-stressed countries. The results of these regressions are depicted in columns 4 and 5, respectively, and here it is that we indeed see significant differences. While the coefficient of the interaction effect remains insignificant when considering the non-stressed countries (Austria, Germany, Finland and France), I find a highly significantly positive effect of the interaction for the group of stressed countries (Italy, Spain and Portugal). The positive coefficient indicates that the expected increasing effect of cash flow on investment is higher if GDP growth in the respective country the firm is located in is higher. This confirms the theory on how macroeconomic shocks influence the distribution of microeconomic determinants of investment. As outlined in figure 3.3, a positive shock shifts this distribution to the right, such that firms want to invest more.

Importantly, this result helps in explaining the divergent paths of aggregate investment across country groups observed in figures 3.1 and especially figure 3.2. Because GDP growth was lower in stressed countries compared to non-stressed countries in the Great Recession and its aftermath, it contributed less to the interaction effect between GDP and cash flow. This non-linear effect amplified the impact of lower cash flow on firm investment, thereby exacerbating the economic downturn in these countries. Accordingly, the interaction between macro- and microeconomic variables constitutes an accelerator mechanism for business cycle dynamics. In addition, also the estimates for the error correction term and the growth in turnover differ across subgroups, with both estimated to be substantially larger for the firms in stressed countries. This indicates a higher sensitivity of investment of these firms to changes in the economic environment, whereas firms in non-stressed countries might be relatively more affected by firm- and country-specific fixed effects and macroeconomic dynamics which are eliminated in the analysis through first-differencing and controlled for by the inclusion of country-year fixed effects, respectively. I also find a significantly positive effect

of financing costs on investment in the non-stressed countries, which is not expected, since higher financing costs should in theory decrease a firm's ability to obtain external funding and thus have a negative effect on investment. One aspect of this result may be that the financing cost variable employed in this analysis does not reflect marginal but average borrowing costs, which may distort the estimation by picking up business cycle information and macroeconomic developments. Scherer (2019) finds similar positive effects of this variable on aggregate investment in a VAR analysis.

Besides the coefficient estimates, it must be noted that the p-value of the Hansen test statistic is very low for the estimate in the non-stressed countries (column 4). However, by opting for the most conservative choices in all model specifications, especially collapsing the instrument matrix by default, I actively push the test results to a higher likelihood of rejection. Being less rigorous by for example allowing for more lags of instruments to be internally generated of course substantially increases the p-values of the Hansen statistic, but this is problematic, as it leads to the negative consequences for the quality of the estimation outlined above. Many analyses, including the ones cited in this paper, circumvent the issue by not reporting the number of instruments and/or not testing the results for reduced instrument counts. By opting for the most conservative choices in all model specifications I try to be strict and transparent in the use of this sensitive class of estimators. In fact, the Hansen statistics themselves can be quite sensitive. For example, eliminating Germany from the sample of non-stressed countries in the regression in column 4 results in a passing p-value of 0.215.

In summary, I find evidence for significant differences in the main variables of the error correction model between the subgroups of stressed and non-stressed countries. While I do not find evidence for a significant effect of the interaction term between cash flow and GDP in the full sample, my results suggests that this effect is indeed present in stressed countries. Both findings confirm the predictions derived from the class of (S, s) models of investment with respect to their implications for the interaction between the micro and the macro level.

3.6 Conclusions

In this paper I utilize a large data set on firms' balance sheet information from different Euro area countries to analyze how interactions between the firm and the aggregate level affect firm investment. Based on the theory of (S, s) models of investment, aggregate shocks should change the distribution of firm-level variables and influence how they affect investment. Therefore, I introduce interaction terms between cash flow as the central variable in the analysis of investment and GDP growth in a dynamic error correction panel model to examine the effects on firm-level investment. Since I find significant differences in the distribution of cash-flow across stressed and non-stressed countries, separate models for the two country groups are estimated.

I find that the effect of cash flow on firm investment indeed depends on GDP growth, confirming the theory of the interaction effect between firm and aggregate level. Crucially, however, I find this interaction effect only for the subgroup of stressed countries. This is of great importance for the evolution of aggregate investment and the observed differences across Euro area countries. Because GDP growth was lower in stressed countries following the Great Recession and its aftermath, the interaction effect created a negative feedback through its effect on firm-level cash flow and thus investment, which in turn exacerbated the comparatively more severe economic downturn observed in stressed countries. This negative feedback can thus in part explain the distinct differences in the evolution of aggregate investment across Euro area countries.

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Appendix

Analysis of aggregate investment

This section provides detailed information on the theoretical derivation and the empirical specification used in the macroeconomic model reported in the introduction.

Estimator and approach

The findings in the introduction require any analysis to take into account the heterogeneity across countries. From the „large N, large T“ literature (see, for example Pesaran & Smith (1995), Pesaran et al. (1999), Bond et al. (2003)) we know that the assumption of homogeneity of the slope parameters is rarely fulfilled under these circumstances, which causes inconsistency of standard fixed effect panel estimators. The Pooled Mean Group (PMG) estimator of Pesaran et al. (1999) addresses this problem by estimating a panel model in error correction specification, allowing for group-specific short-run adjustment parameters, but restricting the long-run coefficients to be identical across groups. This assumption is justified for in general homogeneous groups like members of the Euro area, where the long-run investment relationship is likely to be reasonably similar across countries, as they all are OECD countries with comparable technological development, are subject to the same monetary policy, share the same fundamental Western-European culture and history and are also engaged in a decade-long assimilation process through the European Union.⁵ In addition, as pointed out in the introduction, the main source of heterogeneity in aggregate investment (figure 3.1) is not between countries, but rather between the two sub-groups stressed and non-stressed countries. Estimating the model separately for the two sub-groups therefore further strengthens the plausibility of identical long-run parameters. Estimating the models allows to test whether the long-run equilibria are identical or not, giving rise to an important question regarding the different evolution of aggregate investment: Do the countries actually

⁵ In the empirical part of their original paper developing the PMG estimator Pesaran et al. (1999) take the assumption of identical long-run parameters to be fulfilled on account of the fact that all countries in their (global) sample are OECD members.

recover differently from the recent crises or are the short-run dynamics the same across the Euro area, but the long-run equilibria are different? In the first case it may be relatively easy and reasonable for policy makers to specifically support those countries with a slow recovery as to ensure all member countries return to the same homogeneous growth path, thereby reducing heterogeneities across countries. In the latter case, however, the two country groups would exhibit different long-run equilibria and thus would diverge even further, unless the long-run equilibria themselves can be altered.

Theory

The selection of variables for the macroeconomic analysis is based on the standard medium-sized DSGE model as developed by Christiano et al. (2005) or Smets & Wouters (2005) and Smets & Wouters (2007). In this class of models households own the capital stock and optimally choose their investment in capital goods which are then rented as capital services for production to the firms. Specifically, consider Smets & Wouters (2007), equations 3 and 4 (p.589). Based on the investment Euler equation from household optimization they derive the following theoretical investment function

$$i_t = i_1 i_{t-1} + (1 - i_1) E_t i_{t+1} + i_2 q_t + \epsilon_t^i, \quad (3.7)$$

where i_{t-1} is investment in the last period, $E_t i_{t+1}$ is expected next period investment, q_t is the real value of the existing capital stock, ϵ_t^i is a shock to the investment-specific technology process and i_1 and i_2 are parameters.

q_t in turn is given by

$$q_t = q_1 E_t q_{t+1} + (1 - q_1) E_t r_{t+1}^k - (r_t - E_t \pi_{t+1} + \epsilon_t^b), \quad (3.8)$$

such that the real value of the existing capital stock depends on the expectation of its own value in the next period ($E_t q_{t+1}$), the expected real rental rate on capital ($E_t r_{t+1}^k$), the ex-ante real interest rate ($(r_t - E_t \pi_{t+1})$) and a shock to the risk premium (ϵ_t^b). q_1 is a parameter (for details on the equations and the parameters, see Smets & Wouters (2007)).

Accordingly, investment depends on

$$i_t = i_t(i_{t-1}, E_t i_{t+1}, E_t q_{t+1}, E_t r_{t+1}^k, (r_t - E_t \pi_{t+1}), \epsilon_t^b, \epsilon_t^i) \quad (3.9)$$

The mapping between the determinants of investment in equation 3.9 and observable variables for the empirical specification is based on the following considerations. First and naturally, the correspondent of theoretical investment is aggregate gross fixed capital formation. Second, expected next period investment is proxied by gross domestic product and capacity utilization. The reasoning behind this choice is that aggregate demand and current capacities in production in combination capture the desired level of future investment. Third, by the same line of argument, the current value of productive capital in combination with gross domestic product is taken as the expected future real value of capital. Given the slow moving changes in the value of productive capital, this seems to be a reasonable proxy. Fourth, for the financing cost block in the model - the expected real rental rate on capital ($E_t r_{t+1}^k$) and the ex-ante real interest rate ($r_t - E_t \pi_{t+1}$) - I take the bank lending rate of the ECB. Fifth, the risk premium disturbance is in its essence an uncertainty shock, which I capture by the composite indicator of systemic stress (CISS) of Hollo, Kremer & Lo Duca (2012). Finally, I include total factor productivity as measure of the investment-specific technology disturbance. Investment, gross domestic product and the value of the capital stock are all in real terms. Detailed information on the macroeconomic variables used in the analysis is presented and summarized in table 3.2.

In addition to the variable correspondences above, I consider the time-to-build characteristic of investment to be an important specific for the empirical analysis. As introduced by Kydland & Prescott (1982), given the delay between the decision of a firm to invest and the time the new capital is ready and in place to be used in production, the quarter in which the change in aggregate investment is observed is assumably based on information at least a quarter before.

Taking the variable mapping and the time-to-build argument into account suggests the following investment function

$$I_{it} = I_{it-1} + GDP_{it-1} + CU_{it-1} + K_{it-1} + R_{it-1} + CISS_{it-1} + TFP_{it-1}, \quad (3.10)$$

Table 3.2: Macro-level variables used

Variable	Description	Unit	Transformation	Source
I	real investment	2005=100	–	Eurostat
GDP	real GDP	2005=100	–	Eurostat
CU	capacity utilization	percent	–	Eurostat
K	value capital stock	2005=100	cubic interpolation, divided by GDP deflator	OECD
BLR	bank lending rate	percent	divided by GDP deflator	ECB
CISS	composite indicator of systemic stress		–	Hollo et al. (2012)
TFP	productivity	2005=100	cubic interpolation	AMECO

where I represents real investment, GDP real gross domestic product, CU capacity utilization, K the real value of the capital stock, R the bank lending rate, $CISS$ the composite indicator of systemic stress and TFP total factor productivity.

Applying the error correction transformation of the PMG estimator to equation 3.10 yields the equation to be estimated:

$$\begin{aligned}
 \Delta I_{jt} = & -\phi_j(I_{jt-1} - \theta_1 I_{jt-2} + \theta_2 GDP_{jt-2} - \theta_3 CU_{jt-2} - \theta_4 K_{jt-2} - \theta_5 R_{jt-2} \\
 & - \theta_6 CISS_{jt-2} - \theta_7 TFP_{jt-2}) \\
 & + \beta_{1j}\Delta I_{jt-1} + \beta_{2j}\Delta GDP_{jt-1} + \beta_{3j}\Delta CU_{jt-1} + \beta_{4j}\Delta K_{jt-1} + \beta_{5j}\Delta R_{jt-1} \\
 & + \beta_{6j}\Delta CISS_{jt-1} + \beta_{7j}\Delta TFP_{jt-1},
 \end{aligned} \tag{3.11}$$

where ϕ_j is the country-specific error correction speed of adjustment coefficient, θ_i , $i = 1, \dots, 7$ are the coefficients of the variables in the long-run relationship describes above and β_{ij} , $i = 1, \dots, 7$ are the corresponding country-specific short-run adjustment coefficients. Details of the macroeconomic variables used are summarized in table 3.2

Results

Results are presented in table 3.3.

Column 1 contains the results of the baseline estimation for the full sample of seven countries. The long-run error correction coefficients in the top half are restricted to be the same in each country. Investment increases with last period investment and GDP, while it declines with the degree of capacity utilization, the value of the capital stock, the cost of borrowing and the index of systemic stress as a measure of uncertainty. Turning to the averaged short-run adjustment coefficients in the lower half we find the speed of adjustment parameter ϕ to be estimated significantly negative, as expected, thus confirming the correctness of the error correction specification. The remaining estimates show that investment in the short-run increases with positive changes in last period investment, GDP and the value of the capital stock. The coefficients of the change in capacity utilization and systemic stress are negative. Changes in the cost of borrowing and TFP have no significant effect.

As emphasized above, however, the heterogeneity between country sub-groups suggests analyzing the determinants of aggregate investment separately for stressed and non-stressed countries, thereby allowing for group-specific long-run equilibria. To this end, columns 2 and 3 contain the results for the group of non-stressed and stressed countries, respectively.

Comparing the long-run coefficients reveals the differences between both country groups: the positive effect of GDP and the negative effects of the costs of borrowing as well as systemic stress on investment are much larger for the non-stressed countries. These differences are statistically significant. Moreover, the long-run coefficient of the value of the capital stock has a significant (negative) impact only for stressed countries, while capacity utilization is estimated to have a significantly negative effect only for the non-stressed countries.

Similar differences can be found when considering the short-run adjustment coefficients. The reaction of investment to a change in GDP is almost thrice as large in the stressed countries and changes in the cost of borrowing are only significant for the non-stressed countries. Also note that the speed of adjustment coefficient is only significant for the group of non-stressed countries.

A likelihood-ratio test rejects the H_0 of equal log-likelihoods of the separate regressions in favour of the H_a of significant higher log-likelihood, indicating that the differences between country sub-groups are too large and require separate regressions.

Taken together, the results confirm that the set of long-run coefficients are distinctly different between stressed and non-stressed countries.

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Table 3.3: Results of macro estimation

Dependent variable is the difference of investment

Variable	Full sample	Non-stressed	Stressed
long-run (EC)			
I_{t-2}	0.889*** (0.0234)	0.803*** (0.0428)	0.936*** (0.0122)
GDP_{t-2}	0.145*** (0.0354)	0.221*** (0.0710)	0.0704*** (0.0202)
CU_{t-2}	-0.0342*** (0.0115)	-0.0839** (0.0331)	-0.00911 (0.00795)
K_{t-2}	-0.0430*** (0.00994)	0.00222 (0.0336)	-0.0215*** (0.00623)
R_{t-2}	-0.0612** (0.0285)	-0.430*** (0.140)	-0.0384** (0.0158)
$CISS_{t-2}$	-0.471*** (0.132)	-1.541** (0.644)	-0.182** (0.0772)
TFP_{t-2}	0.0366 (0.0346)	0.00344 (0.0909)	0.0232 (0.0217)
short-run			
ϕ	-4.114*** (1.594)	-2.157*** (0.494)	-9.794 (6.544)
ΔI_{t-1}	3.613** (1.451)	1.695*** (0.311)	9.101 (6.268)
ΔGDP_{t-1}	1.535*** (0.441)	0.866** (0.383)	2.299*** (0.625)
ΔCU_{t-1}	-0.175* (0.104)	-0.256 (0.167)	-0.0713 (0.0948)
ΔK_{t-1}	8.723* (4.679)	22.97*** (6.197)	14.87 (11.36)
ΔR_{t-1}	-0.475 (0.502)	-0.527* (0.316)	-1.104 (1.080)
$\Delta CISS_{t-1}$	-4.150** (1.665)	-3.904** (1.946)	-4.695* (2.595)
ΔTFP_{t-1}	0.00699 (1.290)	1.252*** (0.478)	-2.001 (2.606)
cons	-4.544 (3.872)	4.223 (3.788)	-13.66 (10.65)
N	392	224	168
ll	-619.6	-362.4	-245.8

Notes: Dependent variable is the difference of investment. Marginal effects reported in all columns with standard errors in parentheses. Statistical significance at the 10, 5, 1 percent levels denoted by *, **, ***, respectively.

Firm-level analysis

Table 3.4: Descriptive statistics of micro-level variables

Variable	n	mean	sd	p10	p25	median	p75	p90
full sample								
investment ratio	2007054	74.24	67.36	-0.19	1.01	8.39	29.67	78.60
cash flow ratio	2005941	65.53	23.79	-0.24	6.14	18.21	44.39	104.65
financing costs	2296460	2.37	1.66	0.50	1.09	2.08	3.29	4.59
non-stressed								
investment ratio	263140	42.80	12.47	0	2.37	11.02	31.65	71.43
cash flow ratio	262354	86.73	7.28	4.69	14.66	32.93	70.42	1.54
financing costs	296140	1.96	1.51	0.38	0.82	1.63	2.74	3.95
stressed								
investment ratio	1743914	78.98	72.10	-0.34	0.85	8.00	29.31	80.00
cash flow ratio	1743587	62.34	25.36	-0.81	5.46	16.42	40.54	96.97
financing costs	2000320	2.43	1.67	0.53	1.15	2.15	3.37	4.67
Austria								
investment ratio	1063	40.26	4.06	0.40	4.27	13.31	26.94	51.60
cash flow ratio	1063	114.30	8.80	3.99	13.37	26.73	61.63	161.08
financing costs	1190	1.68	1.43	0.13	0.57	1.40	2.40	3.49
Germany								
investment ratio	22802	82.26	39.09	0.54	4.33	12.03	29.03	59.41
cash flow ratio	22016	72.71	6.56	3.58	9.10	21.78	47.23	109.56
financing costs	25690	2.78	1.87	0.48	1.36	2.64	3.85	5.00
Spain								
investment ratio	671992	51.65	28.78	-1.43	0.15	5.05	21.35	60.81
cash flow ratio	671669	47.57	11.27	-1.33	5.03	14.13	32.23	70.40
financing costs	778770	2.60	1.68	0.64	1.32	2.35	3.57	4.84
Finland								
investment ratio	20528	35.05	2.04	0	1.24	9.83	30.92	70.98
cash flow ratio	20528	56.95	3.99	3.86	11.65	25.00	47.56	94.70
financing costs	23430	2.75	1.62	87.72	1.56	2.52	3.67	4.84
France								
investment ratio	218747	39.42	5.23	0	2.27	10.98	32.08	72.78
cash flow ratio	218747	90.81	7.57	5.19	15.84	35.29	75.00	162.69
financing costs	245830	1.80	1.41	0.36	0.75	1.48	2.50	3.65
Italy								
investment ratio	1015340	98.56	91.48	0	1.63	10.34	34.89	93.41
cash flow ratio	1015340	72.53	31.17	-0.50	5.63	18.18	46.67	115.38
financing costs	1157350	2.28	1.63	0.46	1.03	1.99	3.18	4.47
Portugal								
investment ratio	56582	52.12	14.58	0	1.24	8.82	30.00	77.25
cash flow ratio	56578	54.80	29.78	0.68	8.75	20.97	45.45	96.79
financing costs	64200	2.99	1.91	0.78	1.55	2.68	4.08	5.56

Notes: Investment ratio is investment divided by the capital stock and cash flow ratio is cash flow divided by the capital stock. p10, p25, p75 and p90 refer to the 10%, 25%, 75% and 90% percentile, respectively, of the corresponding distribution. Mean and percentiles in percent, i.e shares are multiplied by a factor of 100.