Follow-thy-neighbor? Spillovers of asset purchases within the real sector*

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Abstract

Does zombie lending due to Unconventional Monetary Policy induce spillover effects between firms? By exploiting the first asset purchase program of the ECB, this paper investigates whether firms linked to banks which benefit from asset purchases induce spillovers on firms without such links. Ignoring spillovers, there is no difference between treated and control group. Taking spillovers into account shows that treated firms invest less and induce negative spillovers on firms operating in the same sector and region. The paper shows the importance to consider spillover effects when assessing unconventional monetary policy: when neglected, spillovers can cover up direct effects.

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1 Introduction

Does unconventional monetary policy (UMP) induce spillover effects among firms operating in agglomerates? Acharya et al. (2019) find a zombie lending behavior of banks exposed to the Outright Monetary Transaction Program (OMT) of the ECB in 2012. They show that firms borrowing from OMT banks do not change their investment behavior, and there is only weak economic growth. An alternative explanation for the sluggish recovery during the sovereign debt crisis could be that zombie lending due to OMP causes spillover effects between market participants and thereby thwarting innovative processes in the economy.

In this paper I propose to enhance Acharya et al. (2019)'s analysis to come to a more comprehensive conclusion about the effects of UMP on firm investment behavior by taking spillover effects between firms which operate in agglomerates, i.e. in regions within sectors, into account. This paper asks the question whether there are spillover effects of the ECB's first large asset purchase program, the securities markets program (SMP), on investment decisions of German small and medium-sized enterprises (SMEs) operating in the same sector within the same region. "Treated firms", i.e. firms with a link to a regional bank which held SMP eligible assets, benefit from increases in loan supply. To assess the real effects, I apply Berg et al. (2021)'s technique and compare investment behavior of treated firms to firms linked to banks which do not benefit from the SMP ("non-treated firms") while taking spillover effects between the two group of firms into account. On the one hand, concurrent spillovers can occur due to local aggregate demand effects, due to agglomeration spillovers or because firms use neighboring firms as a source of information. On the other hand, there could be diametrical spillovers because treated firms benefit from relatively lower financing costs and thereby crowd-out competitors (Benoit, 1984; Combes and Gobillon, 2015; Bustamante and Frésard, 2020).

As a pre-requisite of my study, I replicate Koetter (2020)'s finding that regional banks increase loan supply to corporate borrowers. In particular, I find that low leveraged firms receive more lending, but also high leveraged firms linked to weakly capitalized banks, the "zombie connection". On that basis I study the impact on investment behavior of firms. In the aggregate, I find that regions in which many firms were exposed to the SMP via their bank do not differ in terms of economic growth- similar to Acharya et al. (2019)s' finding. In contrast, I find that high exposed regions show relatively lower unemployment rates in the post period.

Then I move to the firm level and find that if spillovers between firms are ignored, there is no difference in investment decisions between treated and control group observable. In contrast, when taking spillovers into account I find that treated firms reduce their investment activities compared to non-treated firms. The relative reduction amounts to around 50% of average investment activities in the whole sample. There are concurrent spillover effects on non-treated firms: they also invest less the higher the share of treated firms in their surroundings. A non-treated firm which operates in an averagely affected region–sector cluster reduces investments compared to non-treated firms without affected firms in their surroundings. The relative reduction in investments amounts to by around 30% of average investments in the whole sample. The results are in line with previous findings that firms are sensitive to the investment decision of neighbouring firms in the same industry, i.e. peer firms, and synchronize investment behavior (Bustamante and Frésard, 2020; Beck et al., 2020; Fracassi, 2017; Dougal et al., 2015).

Further, I find that profits shrink for firms with many treated peers, and also their market shares are reduced. Instead of investing into fixed assets, treated firms increase their financial claims vis-a-vis other firms and customers, and also increase their workforce.

This paper discusses three possible channels through which negative spillover effects might materialize: (1) Due to local aggregate demand effects, peer firms can be forced to reduce investments as well. I test whether non-tradeable industries drive the effect which would hint at local aggregate demand effects. There is no difference between tradeable and non-tradeable industries, hence I conclude that local aggregate demand effects cannot be the sole driver for negative spillovers on non-treated firms. (2) Weakened agglomeration spillovers such as less benefits from lower transportation costs or infrastructure can be at work, as well as less knowledge spillovers. I argue that the first two rather materialize in the medium to long run and hence probably cannot be seen in my short sample period. For the latter I find that spillovers are not mainly driven by high-tech industries which are considered to comprise mainly high-skilled labor for which knowledge spillovers should matter. (3) Firms can use their peers as a source of information. I cannot rule out that this channel is at work. In fact, Bustamante and Frésard

(2020) argue that especially small firms, which comprise my sample, have less precise information and depend on their peers in judging about their future prospects.

There are two papers which consider spillover effects of UMP. Grosse-Rueschkamp et al. (2019) find that as a response to the corporate sector purchase program, small firms benefit from increased lending by their banks. The positive effect is induced by spillovers of large firms within the same bank which issued more bonds and freed up bank lending resources. Acharya et al. (2019) also investigate possible negative effects of zombie firms on their surroundings. They find that a larger share of zombie firms prevents healthy firms from investing and employing more. Schivardi et al. (2020) point to methodological difficulties when measuring the impact of the share of weak firms on neighboring strong firms: the share of weak firms is correlated with shocks that changes the performance of both groups.

My study contributes to these papers by explicitly assessing spillovers *between firms*. I make use of a credit supply shock, which is exogenous to bank lending for German regional banks and investment decisions of firms linked to these banks. This allows me to study the effect of UMP on investment behavior of firms, and to draw conclusions about spillovers within region–sector clusters, while avoiding identification issues raised by Schivardi et al. (2020).

There are several papers which show intended and unintended effects of the SMP. Researchers agree on that the SMP was successful in lowering government bond yields (Doran et al., 2013; Casiraghi et al., 2016; Gibson et al., 2016; Eser and Schwaab, 2016; Ghysels et al., 2016; De Pooter et al., 2018). Concerning effects on banks and firms, Koetter (2020) shows that regional banks increase commercial lending as a response to the program and Cycon and Koetter (2015) find that corporate refinancing costs decreased. To the best of my knowledge, my paper is the first to study spillover effects of the SMP on firms operating in the same sector and region.

2 The economic mechanisms behind spillovers and hypotheses

In the following I discuss different economic mechanisms which can lead to spillover effects between firms. The discussion shall provide guidance for how to test empirically channels through which spillovers might occur. Then I suggest testable predictions.

2.1 Discussion on the economic mechanisms behind spillovers

Given that firms compete or agglomerate within sectors or within regions, there are at least three possibilities to model spillovers: within industry, within region, or within region–industry.

Local aggregate demand effects such as higher demand for the bakery because the local manufacturer increases her production site, can arise locally across and within industries (Shleifer and Vishny, 1988; Huber, 2018). Agglomeration spillovers, such as technology or knowledge spillovers, or lower transportation costs (Combes and Gobillon, 2015) also arise locally, for instance within the local commercial area in which the manufacturer has expanded. They mainly materialize within the same industry, but could also run across linked industries, for instance which are connected via input-output relationships. Spillovers due to the usage of peer firms as a source of information about own future prospects arise locally according to Dougal et al. (2015), but also across product market peers according to Bustamante and Frésard (2020). There can also be diametrical spillovers which arise due to competition. For instance, firms which are product market competitors might compete within industries, but also within regions within industries.

In this paper, I model spillovers between firms within region–sector clusters. This dimension can pick up agglomeration spillovers, spillovers due to the usage of peer firms as a source of information or spillovers due to competition in factor markets concerning capital goods and product markets. I refrain from modelling spillovers solely within industry as the core of this paper is to assess spillovers between SMEs, which mostly operate locally. Moreover, Dougal et al. (2015) finds that even large public US firms are influenced in their investment decisions by firms which are geographically close to their headquarter. I refine the analysis by modeling spillovers alternatively also within clusters of industries which are linked by input-output relationships within the same region.

Though local aggregate demand effects most likely run across industries, they can still be contained in spillovers within region–industries. To draw conclusions on whether local aggregate demand effects or agglomeration spillovers drive my results, this paper provides several tests. I compare results with and without region–time fixed effects to judge on the role of local aggregate demand effects which affects all firms in one region across industries equally. Note that region–time fixed effects do not control for local aggregate demand effects which affect non-treated and treated firms differently or which affect firms from different industries differently. Hence, I also test whether effects differ for firms producing tradeables from firms producing non-tradeables. If spillovers are driven by local aggregate demand effects, results should only hold for non-tradeable industries.

2.2 Hypotheses development

This paper tests the following hypothesis. Firms linked to a bank which held SMP eligible assets experience a positive credit supply shock. Previously binding financial constraints which constrained their capacity might be relieved. Relative factor costs are reduced compared to firms linked to non-treated banks. Treated firms might react in different ways: expanding in size, employing new technologies, decrease product market prices, or they retain earnings, or invest in other financial assets. Further, according to the Slutsky decomposition of price changes into an income and substitution effect, I cannot rule out that firms even substitute capital for labor, and as a result demand less labor.

Agglomeration spillovers happen concurrently, i.e. if some firms increase in size or employ new technologies, there might be positive spillovers on peer firms due to lower transportation costs as well as knowledge and technology spillovers, and if some firms reduce their production site or investments, positive spillovers to neighboring firms are reduced e.g. Combes and Gobillon (2015). Greenstone et al. (2010) show that total factor productivity increases for incumbent firms if there is a new plant opening in their neighborhood. Peer firms benefit from new technology employed and knowledge disseminated by workers, and conversely suffer if the neighboring firms reduces production. There can also be spillovers due to shared information. Bustamante and Frésard (2020) argue that especially small firms could use their peers as a source of information and hence adjust their own investment decisions accordingly.

Additionally, there can be local aggregate demand effects which induce spillovers which are also concurrent to direct effects. Non-treated neighbouring firms benefit from increased demand due to higher wages at treated firms, due to more people in employment, or simply due to expansion of production and hence higher demand for suppliers, and equally face lower demand if neighboring firms reduce their wage bill e.g. Huber (2018).

Hypothesis: There are concurrent spillovers on firms which operate in areas where many other firms benefited from a positive credit supply shock due to the SMP in terms of firm outcomes.

However, there can also be diametrical spillovers due to crowding-out effects. Firms might use their relative advantage in capital costs and oust competitors from their position in the market. Benoit (1984) develops a theoretical model in which he shows that firms which can afford it have incentives to prey on their competitors by lowering product market prices to drive their competitors out of the market. In his model, the financially constrained competitors do not endure and leave the market. Donohoe et al. (2018) examine competitive externalities of a tax cut and find that firms which enjoy lower tax payments pressure their peers and depress their performance. The effect is strongest for peers which are financially constraint and which have similar products.

Further, Caballero et al. (2008) argue that subsidized firms lock-up labor and thereby drive up labor input costs. Peer firms then not only are faced with relatively higher capital, but also higher labor costs.

Alternative Hypothesis: There are diametrical spillovers on firms which operate in areas where many other firms benefited from a positive credit supply shock in terms of firm outcomes.

3 Data and Identification

3.1 Monetary policy shock

The SMP was the first large scale asset purchase program (APP) that was conducted in the Eurozone. The ECB implemented the program in May 2010 and it lasted until September 2012. The ECB started purchasing Portuguese, Greek and Irish sovereign bonds and extended the program in 2011 to Spanish and Italian sovereign debt. They also purchased marketable debt of private entities incorporated in the Euro area, however, as will be described in Section

3.2, this does not affect firms in the sample of this paper which comprises only SMEs. In total, the program had a notional volume of 218 Billion Euro.

The SMP provides a good testing ground for establishing causal links between APPs and lending to firms and further spillover effects. First, in contrast to the Fed, the ECB was hesitating to intervene into financial markets until the SMP was established. Hence, the program was probably not expected by market participants (Stolz and Wedow, 2010). This condition is crucial to avoid self-selection into treatment group of especially risk-prone banks which loaded up with crisis bonds. Second, the SMP was a response to the sovereign debt crisis in Southern European countries and Ireland, and not to events in Germany. Third, the program aimed at lowering government bond yields and not to stimulate credit growth. The ECB describes this in their announcement of the program, and shows actions to keep aggregate reserves holdings stable by implementing sterilization measures. If there are changes in lending behavior in Germany as a response to the SMP, they are unintended side effects as they were neither the aim nor the reason for the program.

Data on the SMP purchases comes from the ECB and is combined with Bundesbank data on sovereign bond holdings and is taken from Koetter (2020) and Antoni et al. (2019). The data provides information on whether a bank held SMP eligible assets on a yearly basis. A bank is defined as treated if it held SMP eligible assets in 2010, the first year of the SMP program. The sample covers 1,118 German savings and cooperative banks of which 17.98% are treated. To reduce the probability of a selection bias, i.e., to rule out that banks and thereby also firms selected themselves into the group of the directly treated banks and firms, banks must have held SMP eligible assets in 2010. Banks which purchased assets only from 2011 or 2012 onward belong to the control group. Hence, it is possible that I underestimate the actual effect of the SMP, but I rule out that banks which selected into the treatment group after the start of the program confound my results. The sample comprises only savings and cooperative banks to ensure that banks are not specialized in security trading as are large commercial banks. To verify, I follow Abbassi et al. (2016) to approximate a bank's proficiency in trading. They assume that banks which are members of the German trading platform Eurex Exchange have a trading desk. There are four savings banks in Germany which are members of the Eurex[1]. They are excluded from my sample. In case of duplicates, bank-year observations which are consolidated are dropped to avoid double reporting.

3.2 Firm data

The analyses on spillovers are based on the firm level. The Dafne dataset by Bureau van Dijk provides information on firms' bank links. To approximate lending of the bank to the firm, this paper only makes use of firms with a single bank relationship and assumes that loans on the firms' balance sheets originate from their only bank. 59.05% of firms in the data set have a single bank link. Firm balance sheet data is added from Amadeus by Bureau van Dijk. In the analysis, only SMEs are included due to their pivotal role as an

[1]Kreissparkasse Ludwigsburg, Sparkasse Pforzheim, Kreissparkasse Köln and Hamburger Sparkasse

engine of economic growth, employment and economic stability in Germany (BMWi, 2018). Further, it is essential to rule out confounding factors such as other purchases of securities of the ECB at the same time. SMEs do not tap capital markets and usually do not issue bonds but are bank reliant. To identify SMEs, I use the definition provided by Amadeus: Firms are excluded if they are large or very large according to Amadeus. This concerns firms which have operating revenue >= 10 million EUR, or their total assets are >= 20 million EUR, or they have >= 150 employees. 99.49% of firms in my sample do have less than or equal to 150 employees. To avoid that misclassification by Amadeus confound my results, I leave out larger firms in robustness checks.

Further, as described in Section 3.1, I include only firms with a link to a regional bank. 69.05% of bank links in the overall data set are to savings or cooperative banks, which shows the strong reliance of SMEs on regional banks.

Financial firms are excluded as well as industry sectors that are highly subsidized (agriculture, fishing and forestry), or which are closely linked to the state (health industry, education, and public administration).

The data set comprises 396,908 firms, and 1,325,087 firm-year observations. For detailed description of data cleaning, see Section D in the Appendix. Sample size then is greatly reduced because of the availability of firm level variables to calculate gross investments. All analyses are based on a sub sample of firms which report fixed assets and depreciation to calculate gross investments.

– Insert Table ?? around here –

Table ?? reports summary statistics on the regional and on the firm level and Table 12 in the Appendix provides variable definitions. The analysis encompasses 12,339 SMEs or 42,031 firm-year observations for which I have gross investments available. Gross investments is defined as

$$investments = log[fias + depreciation)]_t - log(fias)_{t-1}. \tag{1}$$

Which is log differences of fixed assets in period t plus depreciation and fixed assets in the previous period. In this manner, also replacement investments which replace depreciated assets are also considered. The median firm has total asset size of around 0.935 million Euro and is 14 years old. I use further variables: first differences of log of current assets debt plus 1 (Δlog(Debt+1)). This shows the role of the firm as an financial mediator and reflects financial obligations that customers or other firms have vis-a-vis firm i. Employment is the number of employees, and Δlog(Empl) the first log differences thereof. The median firm in my sample has 14 employees. *Ebta* is earnings before interest, taxes, depreciation and amortization. I use log differences defined as Δlog(Ebta+1) to measure firms profitability. *Opre* is operational revenues which measures turnover of firm i. I use log differences defined as Δlog(Opre+1). All firm level variables are winsorized at 1% and 99% per year.

Treatment is defined as the following. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010.

It equals 0 for banks that did not hold SMP eligible assets in 2010. 25.5% of firms are directly treated , i.e. $SMP = 1$. To measure spillovers within region-sectors, I define space according to Brakman et al. (2005). They show that agglomerations manifest especially on NUTS-3 level ("Kreis"). Sectors are identified with the two-digit NAICS code. Firms operate in 395 regions and 19 sectors in the analysis. The mean treatment share within region–cluster in 2010, $SMPshare$ is 28.8%.

Alternatively, I define industry clusters according to Kelton et al. (2008) to capture input-output (IO) linkages. They suggest 61 clusters of industries which are linked vertically but also horizontally. I group firms in 60 clusters.[2] Each firm belongs to one industry according to the two-digit NAICS and is included at least in two, at the median in nine and at the maximum in 49 clusters. Note that sample size is reduced to 32,875 firm-year observations, or 9,730 firms, because Kelton et al. (2008) exclude wholesale (NAICS codes 42) and retail trade (NAICS codes 44 and 45) because they are too general to fit into IO categories. I estimate the share of treated firms within the same IO cluster within the same region, excluding firm i. Then for each firm I use the average of all IO clusters the firm operates in within the same region, excluding firm i, to obtain $SMPshare\_IO$. The average treatment share within industry clusters firms i operates in is 29.2%.

I further use the following variables: $Post$ is a binary variable which equals 0 in pre period 2007-2009 and 1 in period 2010-2013. $Non\_tradeable$ is a binary variable which equals 1 for firms which operate in an industry classified as

[2] My sample does not contain firms from cluster 40 "insurance" as I exclude financial firms from my sample.

producing non-tradeables according to Delgado et al. (2014), and 0 otherwise. $High\_tech$ is a binary variable which equals 1 for firms which operate in an industry classified as high-tech according to Kile and Phillips (2009), and 0 otherwise. $High\_tech\_Decker$ is a binary variable which equals 1 for firms which operate in an industry classified as high-tech according to Decker et al. (2020), and 0 otherwise.

Before I estimate the effect on investment behavior of firms within region–sector clusters, I perform aggregate analyses to assess whether GDP growth, measured according to log differences of GDP, and the unemployment rate changes depending on how the region was overall affected. $SMPshare\_region$ is the overall share of *all* firms in the data set affected in region r. The average region has a share of 34.5% affected firms. $SMPshare\_region\_SMEs$ is the share of SMEs affected in region r. Here, on average 17.2% of SMEs are affected. The share is lower than the overall share as SMEs rather bank with regional banks which were less affected by the SMP.

3.3 Identification

To gain an overview about the effect of the SMP on German regions, I follow Huber (2018) and assess first whether the macro economy shows changes in performance conditional on the extent how much regions are affected by the SMP. I therefore estimate the following model:

$$Y_{rt} = \gamma_1 \times \text{SMPshare\_region}_r \times Post_t + \alpha_i + \alpha_r + \epsilon_{rt}. \tag{2}$$

Dependent variable is GDP growth, defined as log differences of GDP, and the unemployment rate of region r in year t. Regions are defined according to the NUTS-3 level. $SMPshare\_region$ is the overall share of treated firms of all firms in region r in year t. Alternatively, I measure the share of treated SMEs per region r in year t ($SMPshare\_region\_SMEs$) .

Next I move to the firm level and assess how individual investment behavior of firms changes conditional on their bank being affected by the SMP and on their surrounding firms within their region–sector cluster. Figure 1 sketches the setting of studying spillover effects between SMEs.

– Insert Figure 1 around here –

Triangles are banks, squares are firms. Savings and cooperative banks operate in one confined region. SMEs have a single link to a regional bank and operate in one sector. I measure spillovers between firms within their specific region–sector cluster, marked with the dotted line. The black triangle is a bank which held SMP eligible assets in 2010 and hence is defined as treated, as well as the firms linked to the bank. I measure spillovers according to the share of treated firms within the cluster excluding $firm_i$. In the sketch, for $firm_{i=1}$ and $firm_{i=2}$ the share of treated firms within the cluster is 0.5. For $firm_{i=3}$ the share of treated firms within the cluster is 1. There can be heterogeneous spillover effects on non-treated and on treated firms, which will be captured in the econometric model.

To assess the effect of the SMP on firms operating in the same sector in close proximity, I estimate the following model which is in the vein of Berg et al.

(2021):

$$
\begin{aligned}
Y_{it} = &\gamma_1 \times \mathrm{SMP}_i \times Post_t \\
&+ \gamma_2 \times \mathrm{SMP}_i \times Post_t \times \mathrm{SMPshare}_i \\
&+ \gamma_3 \times (1 - \mathrm{SMP}_i) \times Post_t \times \mathrm{SMPshare}_i \\
&+ \alpha_i + \alpha_{rt} + \alpha_{kt} + \epsilon_{it}.
\end{aligned} \tag{3}
$$

Dependent variable Y_{it} is investments, as defined in Equation 1 of firm i in year t.

The first line corresponds to a common differences-in-differences estimation: SMP is a binary variable which equals 1 if the firm's bank held SMP eligible assets in 2010, and 0 otherwise. $Post_t$ is an indicator which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. γ_1 shows the direct effect of the treatment on firms linked to a bank which held SMP eligible assets in 2010. $SMPshare_i$ is the share of treated firms in the same region–sector of firm i excluding firm i. γ_2 shows spillover effects on treated firms, i.e. the effect of the $SMPshare$ on firms with SMP=1. γ_3 shows spillover effects on non-treated firms, i.e. firms with SMP=0. As results on lending of banks as a response to the SMP show that there was a re-destribution of lending away from high leveraged firms with high capitalized towards low leveraged firms as well as towards high leveraged firms with low capitalized banks, I further apply a more precise treatment definition. $SMP\_precise$ equals 1 only for firms linked to treated banks which belong to the group of firms which benefit from larger loan supply, i.e. low leveraged firms as well as high leveraged firms linked to low capitalized banks (the so called "zombie connection"), and 0 otherwise. Equally, $SMPshare\_precise$ captures the share of treated firms accordign to the definition of $SMP\_precise$ within the same region–sector of firm i without firm i.

To control for unobserved heterogeneity across firms, firm fixed effects (α_i) are included. Region–time fixed effects (α_{rt}) and industry–time fixed effects (α_{kt}) control for region or industry demand shocks. I use the NAICS code for the industry classification. As the treatment variable $SMPshare$ varies on the region–sector level, standard errors are clustered on the region–sector level.

Appendix E compares Equation 3 to a standard interaction model and gives intuition on the interpretation of coefficients, explaining that Equation 3 does not raise collinearity problems.

Verifying the parallel trend assumption in the pre period of treated and control firms is not easy when arguably the effect of the SMP is more complex due to spillovers and hence there are several treatment and control groups. This paper reports results from a dynamic version of Equation 3 to show that the parallel trend assumption of treatment and control group in the pre period is not violated. To estimate a dynamic regression instead of estimating t-tests only between treated and control groups has the advantage that I can show parallel trends for all three coefficients of interest: direct effect, spillover on treated and spillover on non-treated firms instead of subsuming all in either treated or control group. Further, it allows interpretation on the dynamics of the effects over time:

$$
\begin{aligned}
Y_{it} = {} & \alpha_i + \alpha_{rt} + \alpha_{kt} \\
& + \sum_{\tau=2007, \tau \neq 2009}^{2013} \gamma_{1\tau} \, \left(\mathbf{1}_{t=\tau} \times \mathrm{SMP}_i \right) \\
& + \sum_{\tau=2007, \tau \neq 2009}^{2013} \gamma_{2\tau} \, \left(\mathbf{1}_{t=\tau} \times \mathrm{SMP}_i \times \mathrm{SMPshare}_i \right) \\
& + \sum_{\tau=2007, \tau \neq 2009}^{2013} \gamma_{3\tau} \, \left(\mathbf{1}_{t=\tau} \times (1 - \mathrm{SMP}_i) \times \mathrm{SMPshare}_i \right).
\end{aligned}
\tag{4}
$$

I interact treatment variables with indicators for every year τ from 2007 until 2013 using year 2009 as the base year. In particular, $\gamma_{1\tau}$ can verify that treated and control firms for which $SMPshare = 0$ do not substantially differ in terms of outcome variables in the pre period compared to the base year 2009 conditional on the fixed effect structure. $\gamma_{2\tau}$ can verify that treated firms with low $SMPshare$ and treated firms with high $SMPshare$ do not differ substantially in the pre period compared to the base year 2009. Finally, $\gamma_{3\tau}$ can verify that non-treated firms with low $SMPshare$ and non-treated firms with high $SMPshare$ do not differ substantially in the pre period in terms of outcome variable compared to the base year 2009.

4 Results

4.1 Aggregate Results

Table 2 shows results for estimating Equation 2 with GDP growth and unemployment rate as dependent variable.

– Insert Table 2 around here –

Column I and II report results for GDP growth as dependent variable. Neither when the exposure of regions is measured according to the share of all firms treated, nor when it is measured according to the share of SMEs GDP growth changes. The coefficient are close to zero. Columns III and IV report results with the unemployment rate as dependent variable. The unemployment rate is lower in regions with high exposure compared to regions with low exposure to the SMP. The difference is statistically significantly different at the 1% level. For a region with an average exposure of 34.5%, the unemployment rate is $0.345\times(-\ 2.059) = 0.71$ percentage points lower compared to regions which are not affected by the SMP. Given that the average unemployment rate for the whole sample is 7.04%, this change corresponds to a reduction of the unemployment rate of around 10% for regions which are averagely affected.

The following analysis on the firm level shall provide more evidence on why in the mean GDP growth is not affected, but unemployment is reduced in high affected regions.

4.2 Replicating lending behavior

As a pre-requisite to my study I replicate Koetter (2020)'s finding that regional banks increase corporate lending as a response to the SMP. In particular I want to assess whether also firms from my sub-sample which are linked to a SMP bank benefit from increases in loan supply. In Appendix

F I describe literature, hypotheses, data, and identification. As dependent variable I use first differences of log of long term debt holdings of firms, as well as short term loans. Note that I can only approximate long term and short term loans which originate from banks from observable balance sheet items provided by Amadeus. Similarly to Acharya et al. (2019) and Jiménez et al. (2014), I test whether there is a so called "zombie lending behavior" as a response to the SMP, which implies that especially weak banks increase lending to weak firms. Therefore I follow other authors and use the equity ratio banks as a proxy for the bank's weakness (Jiménez et al., 2014; Schivardi et al., 2020; Acharya et al., 2019; Peek and Rosengren, 2005). I define a bank as weak if it was below the median of the distribution of banks' equity ratios in the pre crisis and pre treatment year 2007.

I define a firm as weak if it is highly leveraged following Schivardi et al. (2017). They claim to measure firms' default risk according to their leverage ratio. See Appendix F for further indication that firm leverage captures well firm vulnerability. I partition my sample at the sixth, seventh and eight percentile and define a firm as weak if it was at or above the respective decile in terms of mean leverage in the pre period within the sector it operates in. I use the mean over the whole pre period as some firms do not report every year and hence I can obtain the highest coverage of firm year observations. Table 11 shows the results for long term debt as dependent variable.

– Insert Table 11 around here –

Column I shows the result for a common differences-in-differences model without interactions. There is no differential effect between treated and non-treated banks in terms of their lending behavior. In column II I show differential effects separately for firms linked to lowly capitalized bank and other firms. Again, there are no differential effects.

From column III onward I report the fully specified models. In column III I define a weak firm as one with a mean leverage ratio in the pre period within the sector it operates in that is equal or above to the sixth decile. There is a positive differential effect on long term debt for firms linked to a treated bank which is highly capitalized (Weak_bank=0) and which belong to lower leveraged firms (Weak_firm=0) compared to low leveraged firms with strong banks which were not treated. The differential effect is positive and statistically significantly different from zero at the 5% level. These firms show higher long term debt growth by 1.503pp. Given that the standard deviation of long term debt growth for the whole sample is 4.115, the differential effect between treated and non-treated firms corresponds to more than 36% of one standard deviation of long term debt growth.

Further, I find that weak firms in general obtain less lending if they are linked to a treated bank. The differential effects is negative and statistically significantly different from zero at the 5% level in columns III and IV, and at the 10% level in column V. The negative effect outweighs the general positive effect (γ_1) on long term lending. However, if weak firms are linked with weak banks, the so called zombie lending relationship, they show *higher* loan growth if their bank is treated compared to weak firms which are linked to non-treated weak banks. The results pertain when I change the definition of weak firms and move up the leverage distribution as I present in column

IV and V. The coefficient is statistically significantly different from zero at the 10% level in all specifications. In total there is a positive effect on the growth rate of long term debt of weak firms linked to weak banks (γ_1 + γ_3 + γ_4 > 0).

To summarize, I find that lending is redistributed among firms: strong firms, i.e. low leveraged firms, receive more lending. Weak firms linked to weak banks, the zombie connection, also received more lending. Weak firms with strong banks however, receive less lending. There is no effect on short term loans.[3]

4.3 Investments

Table 3 shows results for estimating Equation 3 with investments as the dependent variable. The table builds up from a simple differences-in-differences analysis which ignores spillovers, to including spillover effect which are homogeneous for treated and non-treated firms, to the fully specified model as described in Equation 3.

– Insert Table 3 around here –

Column I reports the results from a common differences-in-differences model. There is no differential effects between treated and non-treated firms in terms of their investment behavior. In column II, I add homogeneous spillover effects, i.e. spillovers to all firms within the same region-sector. There is a negative spillover effect to peer firms which is statistically significantly

[3]Results are not reported here.

different from zero at the 5% level. In column III I show results for the fully specified model in which I distinguish between spillovers on treated (γ_2) and non-treated firms (γ_3). Spillover effects are driven only by spillovers on non-treated firms. In column III also γ_1 which captures the direct effect is negative and statistically significantly different form zero at the 5% level. Directly treated firms invest less and their investment behavior spills over to non-treated firms which operate in the same region–sector. In terms of economic magnitude, directly treated firms reduce their investments by 0.153 pp, which compares to mean investments in the whole sample of 0.336. That is, the relative reduction of investments of treated firms amounts to more than 50% of average investments activities. Non-treated firms which operate in an averagely affected region–sector with a SMPshare of 0.290 reduce investments by $0.290 \times 0.350 = 0.102$ compared to non-treated firms without treated peers in their surroundings. That is, non-treated firms in an averagely affected region–sector reduce their investments relative to non-treated firms without treated peers by around 30% compared to average investment activities.

In columns IV-VI I apply a more precise definition of the treatment. In the replication exercise on the lending behavior of banks as a response to the SMP, I show that there was a re-distribution of lending supply away from high leveraged firms with strong banks towards low leveraged firms in general, and high leveraged firms with weak banks (see Section 4.2). Following this finding, I define in columns IV -VI firms only as treated if they benefited from higher loan supply, which are the low leveraged firms as well as firms from what I call the "zombie connections". As the treatment becomes more precise, the results also improve in precision: there is a negative direct effect which pertains across all specifications, though it becomes larger in the full model with all possible spillovers. Directly treated firms invest less, and the negative coefficient is statistically significantly differently from zero at the 1% level. The negative spillover effects also become more negative and are statistically significantly different from zero at the 1% level in column VI. In terms of economic magnitudes, non-treated firms which operate in an averagely affected region–sector with a SMPshare_precise of 0.267 reduce investments by $0.267 \times 0.465 = 0.124$ compared to non-treated firms without treated peers in their surroundings. That is, non-treated firms in an averagely affected region–sector reduce their investments relative to non-treated firms without treated peers by more than 36% compared to average investment activities.

The result that firms synchronize investment decisions is in line with previous findings: Dougal et al. (2015) find for public companies in the US that investment decisions of firms are highly sensitive to their peers' investment choice which operate in the same agglomeration. Similarly, Bustamante and Frésard (2020) provide evidence that firms follow their peers in investment decisions. They argue that firms learn from their peers and use them as a source of information. The sensitivity is especially strong for SMEs. Fracassi (2017) shows that it is actually information sharing among social peers which drives concurrent investment decisions.

As spillover effects run in the same direction as direct effect, a common differences-in-differences specifications without modelling spillovers cannot capture changes in investment behavior. The differential effect between treated and control group does not capture that both group of firms reduce their investment activities. Negative spillovers on the group of non-treated blurs treatment and control group in column I and IV. As there are negative effects on the treated firms, and negative spillover effects on the control group, the effects on the single groups becomes only visible when taking spillovers into account.

Regression models in Table 3 include the whole fixed effect structure. In Table 4 in Appendix A I show results for the model with heterogeneous spillover effects building up on the fixed effect structure. Column I includes firm and time fixed effects, column II additionally industry–time fixed effects. There is a negative direct effect which is significantly different from zero for all specifications at the 5% level. Without including region–time fixed effects as in column I and II, however, instead of observing an negative spillover effect on the non-treated, there is a positive effect on the treated the higher the share of treated peer firms. In fact, region–time effects cover up effects on treated as well as on non-treated firms: all coefficients become smaller (more negative) when region–time fixed effects are included. Region–time fixed effects control for local aggregate demand effects which are similar for all firms within the same region. Hence there are local aggregate demand effects which cover up negative spillovers.

To refine the analysis and to capture IO linkages between firms across industries, I alternatively measure spillovers within IO clusters based on the two-digit NAICS code as defined by Kelton et al. (2008).

– Insert Table 5 around here –

Table 5 reports the results. Similarly to spillovers measured within region–sectors, there is a negative direct effect on investments for treated firms. In contrast to before, effects become even stronger, economically and statistically, when spillovers are measured within IO clusters. There is a positive spillover effect on treated firms which could be induced by local aggregate demand effects which affect all firms operating in the same region. When region-time fixed effects are included from column III onward, the positive spillover effect on treated firms disappears and the negative spillover effect on non-treated firms becomes visible. In the full specification which includes all fixed effects, a directly treated firm invests 0.221 percentage points less compared to a non-treated firm which has no affected firms in its surroundings. Given that mean investments for the whole sample is 0.336, directly treated firms reduce investments relative to non-treated firms by more than 65% compared to average investments activities. Non-treated firms which operate in an averagely affected IO-cluster where 29.4% of firms are exposed to the SMP, reduces investments by $1.302 \times 0.294 = 0.38$ percentage points, which corresponds to a relative reduction of more than 100% compared to non-treated firms with no exposure within their clusters and compared to average investment activities.

Note three shortcomings: First, classification by Kelton et al. (2008) picks up IO linkages across industries – vertical links – , but also *horizontal* links, for instance common suppliers or common customers, which makes interpretation of results as *solely* driven by IO linkages difficult. Second, sample size is reduced by almost 39% as Kelton et al. (2008) leave out industries which are too broad. Third, the definition of IO clusters is based on US industry structures. Applying this classification to German data limits interpretabilty.

4.4 Alternative dependent variables

What do directly treated firms do with the additional borrowing capacity offered by their SMP bank if they even reduce investments? Table 6 shows results from estimating Equation 3 with alternative dependent variables.

– Insert Table 6 around here –

Table 6 shows the results. Directly treated firms shrink in size. They load up on financial claims vis-a-vis debtors if they are exposed to other treated firms in the same region–sector cluster. γ_2 is statistically significantly different from zero at the 10% level, and implies that firms linked to a SMP bank and operate in an averagely affected region–industry increase growth of debt relatively to treated firms without treated peers by 1.898×0.29=0.55 percentage points. Given that average growth of current assets debt is 1.78 for the whole sample, treated firms increase relative debt growth by more than 30% compared to average debt growth in the whole sample. Directly affected firms become financial intermediaries themselves, however only if others in their surroundings do the same. Meanwhile treated firms hoard less precautionary savings and reduced cash.

Also, the higher the share of treated firms within the same region–sector, the lower are profits measured according to earnings before taxes, depreciation, amortization, and interest payments. This holds for treated firms as well as non-treated firms. The higher the share of treated firms in the same cluster, the lower are profits. Given that profit growth on average for the whole sample is 0.053, the relative changes for firms surrounded by many treated firms are substantial. Also statistically they are meaningful: the coefficient for spillovers on treated firms in significantly different from zero at the 1% level, and the coefficient which measures spillovers on non-treated firms is statistically significantly different from zero at the 5% level. Moreover, the higher the share of treated firms within the cluster, the lower are market shares for treated and non-treated firms.[4] Spillover effects are significantly different from zero at the 1% level. These results imply that competition among firms within the same cluster increases such that profits and market shares decrease.

Still the question remains, what do firms do *instead* when they reduce investments? At least directly treated firms which are surrounded by many treated firms within the same cluster increase their work force: spillover effects on treated firms for employment growth is positive and statistically significantly different from zero at the 5% level. Given that average employment growth is 0.028 for the whole sample, treated firms in an averagely affected cluster increase employment by $0.29 \times 0.262 = 0.08$ which implies a relative increase of employment growth which is almost three times as large as average employment growth compared to treated firms without treated peers in their surroundings.

[4] Market shares are measured according to sales of firm i over total sales within the same region–sector, including all firms available in Amadeus.

In Table 7 in Appendix A I show results for alternative dependent variables also with the more precise treatment measures. Results remain robust.

To sum up, firms increase their roles as financial intermediaries and employ more. However, in both cases they only do so in sync with other firms in their surroundings which behave similarly. Competition among firms increases according to shrinking profits and market shares.

4.5 Channels

Why are there negative spillovers on the investment behavior of non-treated firms which operate in the same region–sector cluster? This section discusses three potential channels which could drive my results: (1) local aggregate demand effects, (2) weakened agglomeration spillovers and (3) peers as a source of information.

Local aggregate demand effects. By modelling spillovers within region–industry clusters, I do not pick up spillovers across industries which could be local aggregate demand effects. An exception can be if SMP exposure in region–industry clusters are very similar within regions. This is possible as there are only very few regional banks per region. To control for these local aggregate demand effects which are the same for all units in a region, I include region–time fixed effects. Then direct and spillover effects become stronger, i.e. more negative, in most specifications. This points at regional demand effects which work diametrically to direct and spillover effects. It is possible, hence, that firms which are directly treated and as a consequence strengthen their role as financial intermediaries themselves by extending credit to firms they supply or customers, and which increase their workforce, elicit positive demand effects within the region, which might cover up parts of the negative effects on investments.

As an additional test to differentiate between local aggregate demand effects and agglomeration spillovers, I interact Equation 3 with an indicator variable *non_tradeable* which classifies industries according to Delgado et al. (2014) into industries which mainly produce tradeables versus industries which mainly produce non-tradeables. They classify a sector as tradeable if more than 50% of products are traded. The classification is based on U.S. firms and hinges on the industry structure of the U.S. Hence, interpretation of results when using German data has to be treated with care. 45.2% of firms in the sample are defined as producing non-tradeables. If my model picks up local aggregate demand effects only, I expect that spillovers should be driven by the non-tradeable industries only. Conversely, agglomeration spillovers should also affect tradeable industries.

– Insert Table 8 around here –

Table 8 reports the results. There are negative spillovers to non-treated firms which operate in an industry which produces mainly tradeables. There is no difference to firms operating in sectors that produce mainly non-tradeables. These results underline the conjecture that regression results after including region–time fixed effects are not driven by local aggregate demand effects.

Weakened agglomeration spillovers. Another explanation for synchronized investments decisions are weakened agglomeration spillovers. If directly treated firms invest less, their peers also benefit less for instance from lower transportation costs or better developed infrastructure. However, both channels probably are active rather in the medium or long run. Infrastructure needs time to plan and build, and transportation costs might change if peers close down for instance. However, it is possible that firms benefit less from knowledge spillovers if their peers reduce investments. I follow Lerche (2018) and test whether spillovers are driven by information and communications technology (ICT) heavy industries which are high-skilled labor intensive and which should especially be affected by knowledge spillovers. I use the definition employed by Decker et al. (2020) and categorize 14 industries as high-tech based on four-digit NAICS codes.[5] Alternatively, I use the measure by Kile and Phillips (2009) which is based on three-digit NAICS codes.[6] 8.4% of observations according to the definition used by Decker et al. (2020), and 14.2% of observations according to the definition by Kile and Phillips (2009) belong to high-tech industries.

I report the results in Table 8 columns II and III. As before there are negative direct effects on treated and negative spillover effects on non-treated firms. Triple and quadruple interactions with *high_tech* are not statistically significantly distinguishable from zero. This result holds for both classifications of ICT industries. There are no differential effects for firms operating

[5] NAICS 3254, 3341, 3342, 3344, 3345, 3364, 5112, 5161, 5179, 5181, 5182, 5413, 5415, 5417, definition provided by Heckler (2005).

[6] Ten three-digit NAICS identify high-tech industries: 325, 334, 335, 339, 511, 513, 514, 517, 518, 541.

in high-tech industries. Hence, I cannot rule out that it is not knowledge spillovers which drive my results.

Peers as a source of information. Another driver for concurrent spillovers on investments could be shared information. Bustamante and Frésard (2020) find that especially smaller firms in their sample, which composes US publicly-listed firms only, possess less precise information about their future prospects and hence use peer firms as a source of information for their investment decisions. It might be that as my sample composes only of SMEs that non-treated firms use the reduction in investments as a source of information for their own prospects and hence follow their peers. Also, SMEs in my sample operate within the same region in the same sector and hence it might also be that they have personal ties. In fact, Fracassi (2017) find that social ties between firm managers drive synchronized investment behavior, though again their study is on a sample of public companies only. Further, null results on sales as an alternative dependent variable might hint at an information channel: if, for instance, firms reduced demand for supplies, suppliers would reduce sales as a response. However, as can be seen in Table 6 column V, there are no differences in terms of sales for directly treated firms.

5 Robustness

For robustness, I discuss three concerns and propose tests to rule out that these drive my results: (1) different time trends, (2) SMP_share is correlated with regional characteristics and (3) time-varying bank characteristics.

(1) There are no different time trends. If treatment and control group show different time trends, the important parallel trend assumption for estimating a differences-in-differences model is violated. In order to test the parallel trend assumption between treated and control group in the pre period, and to assess the dynamics of the effects on investments in the post period, Figure 2 presents coefficient plots from estimation the dynamic regression Equation 4 with investments as dependent variable.

– Insert Figure 2 around here –

Panel 2a shows the evolution of the coefficient for the direct effect $\gamma_{1\tau}$. The regression estimation compares differences between treated and control group to the base year 2009. Confidence intervals are plotted at the 1% level. Differences between the two groups are close to zero in the pre period. In the post period, investments for treated compared to non-treated firms are lower especially in 2011, at the height of the SMP.

Panel 2b shows the evolution of the coefficient for the spillover effect on treated firms $\gamma_{2\tau}$. Differences between the two groups are close to zero in the pre as well as in the post period. Panel 2c shows the evolution of the coefficient for the spillover effect on non-treated firms $\gamma_{3\tau}$. Non-treated firms with low exposure do not differ from non-treated firms with a high SMP exposure from neighboring firms in the pre period. In the post period, the coefficient for spillovers on non-treated firms is negative from 2011 onward.

(2) SMPshare is not correlated with regional characteristics. Another concern might be that the share of treated firms, $SMPshare$, is correlated with regional characteristics in the pre period and hence merely depicts differences across German regions. If these regions then develop differently according to these characteristics, my results cannot be ascribed to the SMP treatment, but merely to regional differences which coincide with my treatment status. Figure 3 shows correlations of regional characteristics with treatment status over time. I distinguish between high and low treated regions according to the mean of the $SMPshare$ per region. Regions are defined as high treated if their mean $SMPshare$ is above the median of all regions, and as low treated otherwise.

– Insert Figure 3 around here –

Panel (a) plots GDP per capita, and Panel (b) GDP growth over time including confidence bands at the 95% level. There are no substantial differences between high and low treated regions. If anything, high treated regions show slightly lower GDP per capita in the post period after 2010. In Panel (c) I show correlations of the unemployment rate with treatment status over time. High treated regions have a slightly higher unemployment rate throughout the sample period. However, confidence intervals overlap largely. In Panel (d) I show the the change of the unemployment rate over time. There are no differences between the groups. Finally, Panel(e) depicts differences in industry composition of different regions measured by the share of tradebles. Again, confidence intervals largely overlap for the two groups, and there are no differences in terms of changes of the share of tradeables, as can be seen in Panel (f). Hence I conclude that there are no substantial systemic differences between high and low treated regions. For time-invariant level differences, such as in the unemployment rate, I can control for in the regression models by including firm fixed effects in which region fixed effects are nested as firms rarely change their region.

(3) Spillovers are not driven by time-varying bank characteristics. Spillovers which I observe between firms might be driven by spillovers between treated and non-treated banks within the same region. For instance, a treated bank might increase its market share by offering lower loan rates after benefiting from the SMP program thereby inducing negative spillovers on their competitor bank in the same region. Further, other time-varying bank specific characteristics such as new CEOs which change the lending policy of the local bank during the height of the sovereign debt crisis might confound my results if they are correlated with the treatment status of the bank. And finally, during the pre period, Lehman Brother collapsed which affected some regional savings banks in Germany due to the involvement in the MBS market of their Landesbank (Landesbanken are the central institutions of local savings banks). To control for time-varying bank characteristics, I include bank–time fixed effects to test whether spillovers between firms pertain. The sample size is slightly reduced as singletons are dropped in the regression, i.e. there must be several bank-firm-time observations in order for that bank to be included in the regression.

– Insert Table 9 around here –

Results are reported in Table 9. Spillovers on non-treated firms (γ_3) become just slightly smaller in terms of economic magnitude, and stay robust in terms of statistical significance. Negative spillovers on non-treated firms are not driven by spillovers of confounding factors on the bank level. Note that direct effects are not estimable in this setting as they are collinear with bank-time variations fot the total treatment measures in column I-III. They are estimable in columns IV-VI because SMP banks are included in treatment and control group in case they are strong and serve weak as wel las strong firms.

6 Conclusion

As a response to the SMP, regional bank increase corporate lending (Koetter, 2020). In my sub-sample of German SMEs with single bank links I find that there was a re-distribution of lending sources towards low leveraged firms as well as to high leveraged firms linked to weakly capitalized banks- what I call the "zombie connection". Already Acharya et al. (2019) find that after the OMT announcement of the ECB what followed for European banks is an increase in zombie lending. They also assess investment behavior of firms linked to OMT banks and do not find changes in investment activities. My paper tries to enhance the analysis by taking spillover effects between firms into account. In fact, I find that as a response to changes in lending behavior of banks exposed to the SMP, firms linked to these banks invest less and induce spillover effects on firms operating in the same region–sector clusters. Meanwhile, profits and market shares shrink for firms with a strong exposure to treated firms within their clusters.

This paper shows the importance of taking spillovers into account. Common differences-in-differences estimations yield no results as concurrent spillovers cover up direct effects. In order to gain a more comprehensive understanding of the real effects of unconventional monetary policy, it is necessary to consider that firms are interconnected and react to changes of behavior of their peer firms.

There are several issues which can be researched in the future. In particular, what is the exact kind of spillovers that UMP induces? For instance, are spillovers due to information sharing among peer firms? Do firm managers know each other or do they infer information just by observing other firms? And finally, it could be that UMP, which hits the banks first, also induces spillovers at the bank level. Are there also spillovers between banks operating in the same region on their lending behavior?

Appendices

A Tables

Table 1: Summary Statistics

This table reports summary statistics for regional and firm-level variables over the time period 2007-2013. *GDPgrowth* is log changes of GDP of German NUTS-3 regions. Unemployment rate is also on regional level. *SMPshare_region* is the share of treated firms within regions (treatment defined as below), and *SMPshare_region_SMEs* is the share of SMEs treated within regions. The firm level sample encompasses 12,339 small and medium sized German firms. *Investments* is gross investments defined as log change of fixed assets plus depreciation. *SMP* is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. In *SMP_precise* only firms which benefit from increases in loan supply according to Table 11 are defined as treated. *SMPshare* is the share of treated firms in the same region–sector in year 2010. *SMPshare_precise* captures the share of treated firms based on *SMP_precise*. *SMPshare_IO* is the average share of treated firms within the same input-output clusters according to Kelton et al. (2008). *Post* is a binary variable which equals 0 in pre period 2007-2009 and 1 in period 2010-2013. *Non_tradeable* is a binary variable which equals 1 for firms which operate in an industry classified as producing non-tradeables according to Delgado et al. (2014), and 0 otherwise. *High_tech* is a binary variable which equals 1 for firms which operate in an industry classified as high-tech according to Kile and Phillips (2009), and 0 otherwise. *High_tech_Decker* is a binary variable which equals 1 for firms which operate in an industry classified as high-tech according to Decker et al. (2020), and 0 otherwise. Δtoas is the first difference of log total assets. ΔDebt is first differences of log of current assets debt plus 1. Δcash is first differences of log of cash plus 1. Δebta is first differences of log of earnings before interest, taxes, depreciation and amortization plus 1. Δsales is first differences of log of operational revenue plus 1. *market_share* is the share of sales over total sales of all firms available in Amadeus for the same region-sector of firm i. Δemployment is the first differences of log employment. Investments, firm balance sheet variables, and employment are winsorized at the 1% and 99% per year. Continued next page . . .

	N	mean	sd	min	p50	max
GDP growth	2,726	0.025	0.047	-0.281	0.028	0.409
Unemployment rate	2,726	7.042	3.411	1.200	6.300	22.000
SMPshare_region	2,726	0.345	0.154	0.036	0.318	0.719
SMPshare_region_SMEs	2,726	0.172	0.210	0.000	0.064	0.770
Investments	38,661	0.336	0.660	-1.205	0.158	5.030
SMP	38,661	0.257	0.437	0.000	0.000	1.000
SMP_precise	38,661	0.236	0.425	0.000	0.000	1.000
SMPshare	38,661	0.290	0.302	0.000	0.156	1.000
SMPshare_precise	38,661	0.267	0.293	0.000	0.127	1.000
SMPshare_IO	30,228	0.294	0.294	0.000	0.149	0.995
Post	38,661	0.797	0.402	0.000	1.000	1.000
Non_tradeable	38,661	0.458	0.498	0.000	0.000	1.000
High_tech	38,661	0.141	0.348	0.000	0.000	1.000
High_tech_Decker	38,661	0.083	0.276	0.000	0.000	1.000

Summary statistics continued ...

	N	mean	sd	min	p50	max
Δtoas	38,661	0.038	0.286	-1.132	0.018	1.189
Δdebt	38,536	1.780	4.803	-14.290	0.000	13.727
Δcash	37,337	0.087	1.573	-5.117	0.055	5.366
Δebta	25,259	0.053	0.732	-2.864	0.034	2.697
Δsales	24,664	0.040	0.288	-1.831	0.029	1.667
market_share	32,519	0.032	0.104	-0.002	0.005	1.000
Δemployment	22,103	0.028	0.212	-0.916	0.000	0.981

Table 2: Aggregate analyses

This table reports results from estimations $Y_{rt} = \alpha_r + \alpha_t + \gamma_1 Post_t \times \text{SMPshare}_r + \epsilon_{rt}$. *Post* is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. *SMPshare_region* is the share of firms in region r which are linked to a bank which hold SMP eligible assets in 2010. *SMPshare_region_SMEs* is the share of small and medium sized firms in region r which are linked to a bank which hold SMP eligible assets in 2010. Dependent variables are GDP growth, defined as log differences of GDP of region r in year t in columns I and II, and the unemployment rate of region r in year t in columns III and IV. The regression includes region and time fixed effects. Robust standard errors are clustered on the region level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I) GDP growth	(II) GDP growth	(III) Unemployment	(IV) Unemployment
Post×SMPshare_region	-0.010		-2.059***	
	(0.010)		(0.317)	
Post×SMPshare_region_SMEs		-0.001		-0.691***
		(0.008)		(0.260)
Observations	2,726	2,726	2,726	2,726
R-squared	0.438	0.438	0.972	0.971
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table 3: Direct and spillover effects on investments

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. Column I and IV report results from a common differences-in-differences estimation. Column II and V include homogenous spillover effects, and from columns III and VI show results from the fully spedified model. In columns IV-VI I apply more precise treatment definitions (SMP_precise and SMPshare_precise): only firms which are low leveraged (which belong in the eighth or above decile in terms of mean leverage in the pre period) as well as firms which are high leveraged and linked to weak banks (which belong to the below median capitalized banks in 2007) and which banks held eligible SMP assets in 2010 are defined as treated and count into the share of treated firms. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV) precise	(V) precise	(VI) precise
SMP×Post	-0.049	-0.048	-0.153**	-0.056*	-0.054*	-0.188***
	(0.031)	(0.032)	(0.062)	(0.033)	(0.033)	(0.064)
Post×SMPshare		-0.257**			-0.333**	
		(0.130)			(0.134)	
SMP×Post×SMPshare			-0.122			-0.172
			(0.138)			(0.139)
(1-SMP)×Post×SMPshare			-0.350**			-0.465***
			(0.141)			(0.147)
Observations	38,661	38,661	38,661	38,661	38,661	38,661
R-squared	0.567	0.567	0.567	0.567	0.567	0.567
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Direct and spillover effects on investments- build up of FE

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. The regression builds up on fixed effect structures: column I includes firm and time fixed effects, column II includes industry–time, and column IV region-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV)
SMP×Post	-0.119**	-0.119**	-0.146**	-0.153**
	(0.048)	(0.050)	(0.059)	(0.062)
SMP×Post×SMPshare	0.150**	0.144**	-0.053	-0.122
	(0.064)	(0.067)	(0.128)	(0.138)
(1-SMP)×Post×SMPshare	-0.046	-0.048	-0.280**	-0.350**
	(0.045)	(0.046)	(0.128)	(0.141)
Observations	38,663	38,663	38,663	38,663
R-squared	0.513	0.531	0.548	0.567
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No
Industry-Time FE	No	Yes	No	Yes
Region-Time FE	No	No	Yes	Yes

Table 5: Direct and spillover effects become stronger when measured within input-output clusters

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare\_IO}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare\_IO}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare\_IO$ is the mean of the shares of treated firms in the same input-output clusters according to Kelton et al. (2008) within the same region, excluding firm i. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV)
SMP $\times Post$	-0.168***	-0.180***	-0.208***	-0.221***
	(0.058)	(0.062)	(0.071)	(0.077)
SMP $\times Post \times SMPshare\_IO$	0.234***	0.244***	-0.938	-0.989
	(0.081)	(0.085)	(0.629)	(0.662)
(1-SMP) $\times Post \times SMPshare\_IO$	0.010	0.003	-1.223*	-1.302**
	(0.049)	(0.050)	(0.629)	(0.663)
Observations	30,228	30,228	30,228	30,228
R-squared	0.529	0.547	0.572	0.590
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No
Industry-Time FE	No	Yes	No	Yes
Region-Time FE	No	No	Yes	Yes

Table 6: Direct and spillover effects on other dependent variables

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variables are log differences of total assets, log differences of current assets debt (Δlog(debt + 1)), log differences of cash (Δlog(cash + 1)), log differences of earnings before depreciation, amortization and taxes (Δlog(ebta + 1)), log changes of sales (operational revenues) (Δlog(opre + 1)), the market share defined as sales of firm i over total sales of all firms within region–sector which are available in Amadeus and log differences of number of employees (Δlog(empl)) of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I) Δtoas	(II) Δdebt	(III) Δcash	(IV) Δebta	(V) Δsales	(VI) market_share	(VII) Δempl
SMP×Post	-0.055*	-0.575	0.007	0.075	-0.026	0.001	-0.021
	(0.030)	(0.507)	(0.159)	(0.107)	(0.049)	(0.007)	(0.062)
SMP×Post×SMPshare	0.110	1.898*	-0.765*	-0.670***	-0.118	-0.083***	0.262**
	(0.071)	(1.137)	(0.427)	(0.221)	(0.092)	(0.031)	(0.116)
(1-SMP)×Post×SMPshare	0.024	0.607	-0.647	-0.462**	-0.153*	-0.081***	0.193
	(0.066)	(1.100)	(0.404)	(0.229)	(0.085)	(0.028)	(0.120)
Observations	38,661	38,498	37,133	20,882	19,898	32,152	19,656
R-squared	0.374	0.388	0.268	0.344	0.427	0.887	0.464
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Direct and spillover effects on other dependent variables, more precise treatment measure

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variables are log differences of total assets, log differences of current assets debt (Δlog(debt + 1)), log differences of cash (Δlog(cash + 1)), log differences of earnings before depreciation, amortization and taxes (Δlog(ebta + 1)), log changes of sales (operational revenues) (Δlog(opre + 1)), the market share defined as sales of firm i over total sales of all firms within region–sector which are available in Amadeus and log differences of number of employees (Δlog(empl)) of firm i in year t. *SMP_precise* is a binary treatment variable and equals 1 for low leveraged firms which are linked to banks which held eligible SMP assets in 2010, as well as for high leveraged firms which are linked to weakly capitalized banks which held eligible SMP assets in 2010. *Post* is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. *SMPshare_precise* is the share of treated low leveraged firms and treated high leveraged firms linked to weak banks in the same region–sector, excluding firm i. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I) Δtoas	(II) Δdebt	(III) Δcash	(IV) Δebta	(V) Δsales	(VI) market_share	(VII) Δempl
SMP_precise×Post	-0.054*	-0.038	0.145	0.073	-0.047	-0.001	-0.027
	(0.032)	(0.504)	(0.158)	(0.106)	(0.057)	(0.007)	(0.058)
SMP_precise×Post×SMPshare_precise	0.080	1.615	-1.048**	-0.676***	-0.072	-0.080**	0.188*
	(0.068)	(1.169)	(0.425)	(0.232)	(0.099)	(0.035)	(0.113)
(1-SMP_precise)×Post×SMPshare_precise	-0.001	0.963	-0.754*	-0.504**	-0.156	-0.082**	0.092
	(0.067)	(1.163)	(0.408)	(0.246)	(0.097)	(0.032)	(0.123)
Observations	38,661	38,498	37,133	20,882	19,898	32,152	19,656
R-squared	0.374	0.388	0.268	0.344	0.427	0.887	0.464
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Direct and spillover effects on investments is not different for non-tradeable industries high tech industries.

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–industry, excluding firm i. I further interact all coefficients with an $indicator$, which is $non-tradeable$ in column I. It equals 0 if firm i operates in an industry which according to Delgado et al. (2014) mainly produces tradeables, and 1 otherwise. In column II, $Indicator$ is $High\_tech$ which equals 1 if firm i operates in an ICT intense industry according to Kile and Phillips (2009). In column III, $Indicator$ is $High\_tech\_Decker$ which equals 1 if firm i operates in an ICT intense industry according according to Decker et al. (2020). The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I) *Tradeable*	(II) *High_tech*	(III) *High_tech_Decker*
Post× Indicator	0	0	0
	(omitted)	(omitted)	(omitted)
SMP×Post	-0.132*	-0.136**	-0.150**
	(0.076)	(0.066)	(0.065)
SMP×Post×Indicator	-0.046	-0.089	-0.019
	(0.106)	(0.152)	(0.171)
SMP×Post×SMPshare	-0.157	-0.128	-0.115
	(0.149)	(0.136)	(0.137)
SMP×Post×SMPshare×Indicator	0.086	0.070	-0.115
	(0.139)	(0.213)	(0.253)
(1-SMP)×Post×SMPshare	-0.379***	-0.348**	-0.347**
	(0.146)	(0.142)	(0.142)
SMP×Post×SMPshare×Indicator	0.069	0.063	-0.047
	(0.099)	(0.166)	(0.243)
Observations	38,661	38,661	38,661
R-squared	0.567	0.567	0.567
Firm FE	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes

Table 9: Direct and spillover effects on investments including bank–time fixed effects

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \alpha_{bt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–industry, excluding firm i. The regression includes firm fixed effects, region-time, industry-time and bank-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively. CHANGE TEXT!! NEW

	(I)	(II)	(III)	(IV) precise	(V) precise	(VI) precise
SMP $\times Post$	0	0	0	-0.103	-0.102	-0.218**
	(omitted)	(omitted)	(omitted)	(0.088)	(0.088)	(0.106)
Post $\times SMPshare$		-0.182			-0.180	
		(0.137)			(0.137)	
SMP $\times Post \times SMPshare$			-0.061			-0.021
			(0.160)			(0.150)
(1-SMP) $\times Post \times SMPshare$			-0.278*			-0.338**
			(0.156)			(0.162)
Observations	37,263	37,263	37,263	37,263	37,263	37,263
R-squared	0.628	0.628	0.628	0.628	0.628	0.628
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes

B Figures

Figure 1: Setting

This graph shows the setting of my analysis. Triangles are regional banks which operate in one confined region. Squares are firms which are linked to one bank and operate each in one sector. A bank is defined as being treated if it held SMP eligible assets in 2010, and is makred with black in the graph. Firms linked to treated banks are also defined as directly treated, firms linked to non-treated banks are defined as non-treated. The dotted square shows a region–sector cluster in which three firms operate: $firm_{i=1}$ is faced with treatment share of $SMPshare_i = 0.5$ in its cluster. $firm_{i=2}$ has $SMPshare_i = 0.5$ and $firm_{i=3}$ has an $SMPshare_i = 1.0$.

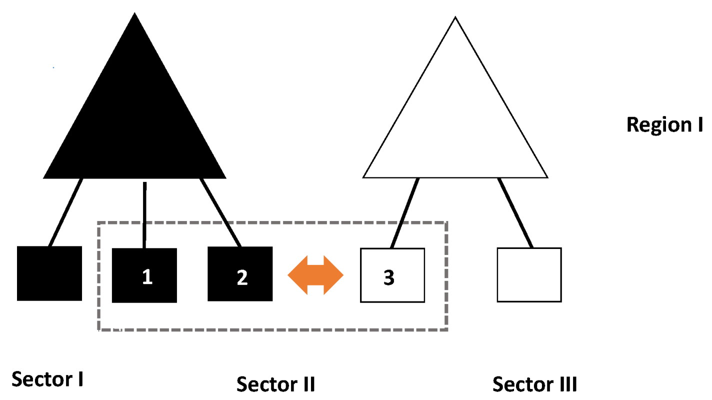
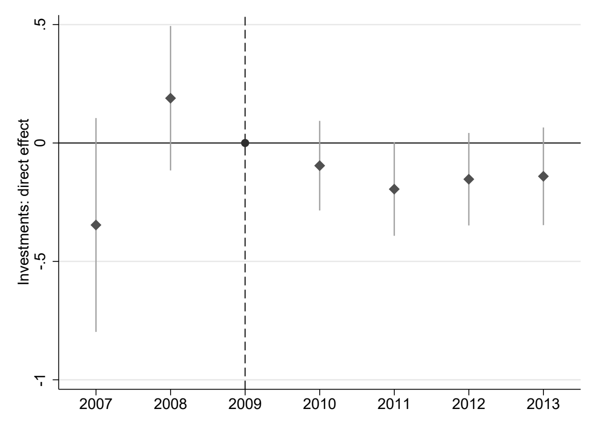


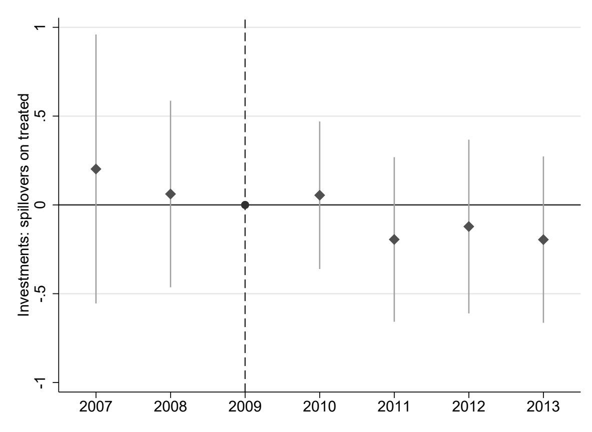
Figure 2: Coefficient plots for investments

These figures show coefficient plots from estimating dynamic Equation 4 in the vein of Berg et al. (2021). Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. I interact with binary variables for every year $\mathbf{1}_{t=year}$ excluding 2009. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–sector level. Panel (a) plots $\gamma_{1\tau}$ for τ=2007 until τ=2013 with $\tau \neq 2009$ which is the direct effect , panel (b) plots $\gamma_{2\tau}$ correspondingly which is the spillover effect on the treated, and panel (c) plots $\gamma_{3\tau}$ correspondingly which is the spillover effect on the non-treated. Confidence intervals are marked at the 1% level.

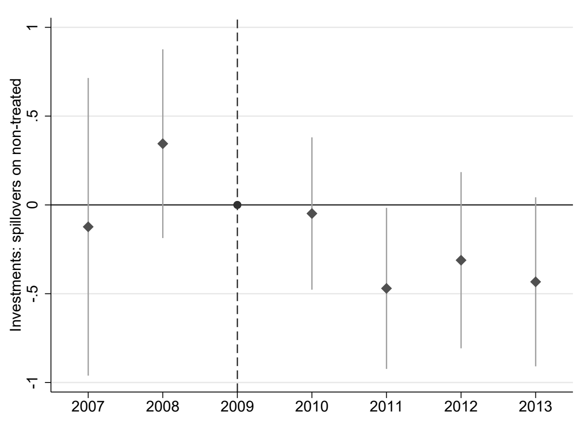
(a) Direct effect: $\gamma_{1\tau}$



(b) Spillover on treated: $\gamma_{2\tau}$



(c) Spillover on non-treated: $\gamma_{3\tau}$

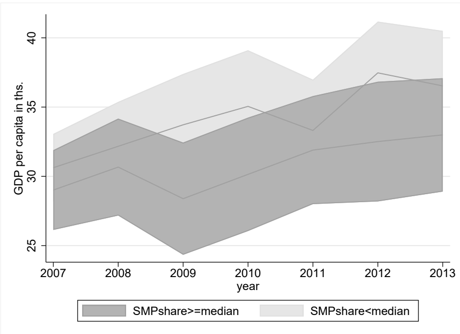


C Regional characteristics

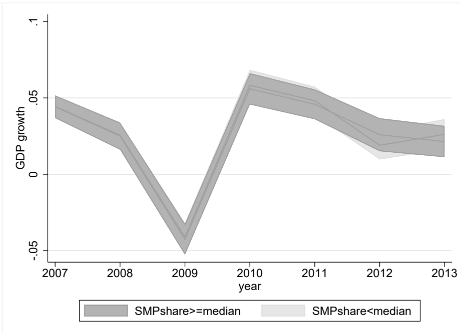
Figure 3: Regional characteristics and treatment status

This figure shows correlations of regional characteristics with treatment status. Regions are defined as high treated if the mean of $SMPshare$ per region is above the median of all regions, and as low treated otherwise.

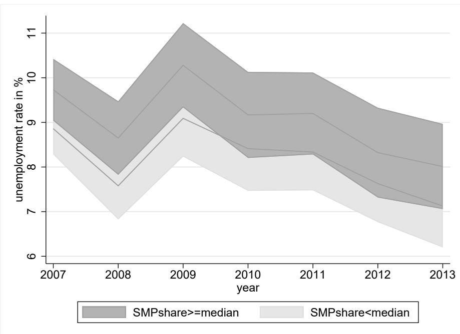
(a) GDP per capita



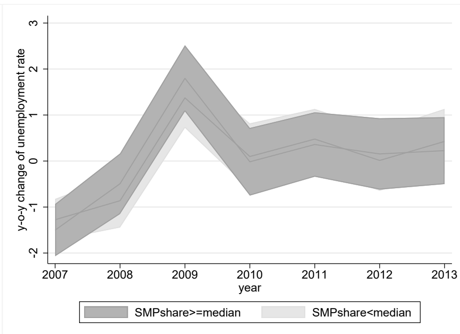
(b) GDP growth



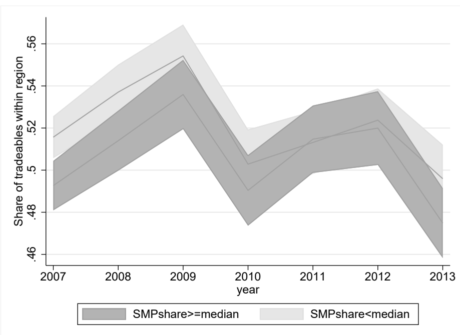
(c) Unemployment rate



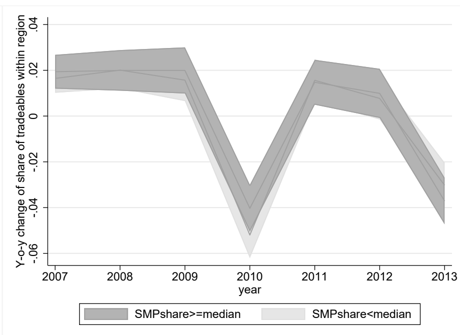
(d) Change of unemployment rate



(e) Share of tradeables



(f) Change of share of tradeables



D Firm level data cleaning

The Dafne data set comprises more than 1.6 million firms during the period 2007-2013. After merging with Amadeus, the data set covers 1,019,047 firms. To derive a consistent data set, further data cleaning on the Amadeus firm financial data set is necessary: If there are firm-year duplicates, I keep the unconsolidated balance sheet information and drop consolidated data. Some firms have the same name but different IDs at Buerau van Dijk. This can be due to mergers. If name of firm, zip code and year is the same, but ID and consolidation code is different, the observations are dropped as I can assume that it is the same firm, but I do not know which report is the correct one. Further, observations with negative total assets are dropped. The age of the firm is calculated as the current year minus the year of incorporation and firms with negative age are dropped.

E Note on Berg et al. (2021)'s regression specification

Berg et al. (2021)'s proposed regression specification is related to a common interaction model. I compare the approach to a standard interaction model and explain how the two relate. The following equation shows a common example of a differences-in-differences specification combined with an interaction model:

$$\begin{aligned} Y_{it} = &\ \alpha_1 \times \mathrm{T}_i \times Post_t \\ &+ \alpha_2 \times \mathrm{T}_i \times Post_t \times \mathrm{M}_i \\ &+ \alpha_3 \times \mathrm{M}_i \times Post_t \\ &+ \cdots + \epsilon_{it}. \end{aligned} \tag{5}$$

Whereby T is a treatment variable, Post indicates a pre - post time dimension, and M is a modifier. This corresponds to T being SMP and M being SMPshare in Equation 3. If we are interested in the marginal effect of M on Y, given that T=1 and Post=1, we derive the following: $\frac{\delta Y}{\delta M|_{T=1,Post=1}} = \alpha_2 + \alpha_3$.

In contrast, the specification by Berg et al. (2021) in Equation 3 displays the marginal effect of M on Y given that T=1 and Post=1 directly with γ_2.

The marginal effect of M on Y given that T=0 and Post=1 corresponds to α_3 in Equation 5, and also can be directly seen in Equation 3 with γ_3. The advantage of Equation 3 over Equation 5 is hence that the effect of the SMPshare (corresponds to M here), is directly displayed for the group of the treated firms and the non-treated firms separately.

To put it differently, Equation 3 splits the effects according to direct effect, effect of M given that T=1 and effect of M given that T=0. In contrast, Equation 5 splits effects according to direct effect, the differential effect of M if T=1 compared to T=0, and the effect of M given that T=0.

F Replication exercise on bank lending

Previous literature finds that UMP has sparked increased bank lending. Koetter (2020) shows that German regional banks increase credit supply to corporate borrowers as a response to the SMP. Jiménez et al. (2014) find that in the low interest rate environment, especially weakly capitalized banks increase lending to low productive units. And Acharya et al. (2019) provide evidence for the so called zombie lending behaviour of European banks after the Outright Monetary Transaction Program announcement by the ECB in 2012. Again, it is the weakly capitalized banks which lend to low productive firms. In the following, I replicate Koetter (2020)'s analysis to assess whether also SMEs from my sub sample which link with regional banks and only have a single bank relationship increase borrowings. In particular, I assess whether there is also a zombie lending behavior as a response to the SMP, i.e. increased lending from weakly capitalized banks to weak firms. Further, firms in this sub sample must report fixed assets and depreciation in order to estimate their gross investments, as well as long term debt. So in contrast to Koetter (2020) I can only see borrowings from a small sub set of firms which makes up the bank lending portfolios.

Hypotheses Exposure to SMP eligible assets is low among German savings and cooperative banks. On first sight, it is not clear why there should be a change in lending activity to firms, and further spillover effects. A bank that held eligible SMP assets could benefit in various ways. Either it sold the asset to the ECB and thereby obtained liquid reserves. Or it could benefit from a valuation effect. There are two building blocks why there could be a change in lending behavior for a specific group of banks: First, according to the zombie lending literature, lowly capitalized banks have an incentive to continue lending to troubled borrowers and thereby bet on the borrower's revival to avoid a loss to the own balance sheet (Caballero et al., 2008). An unexpected windfall gain might enable the bank to do so. Second, according to Diamond (2001), the size of the recapitalization is decisive to a change in behavior of a bank. It is especially these *small* windfall gains which lead to a gamble for resurrection instead of a healthy consolidation of banks' balance sheets (Keuschnigg and Kogler, 2020; Giannetti and Simonov, 2013).

Hypothesis: There is an increase in lending which is driven especially by low capitalized banks to weak firms as a response of the SMP.

On the other hand, it is possible that exposures are very small, and that therefore the effect is so small that it is not perceivable.

Null Hypothesis: There is no change in lending behavior of banks with exposure the SMP.

Data Information on the bank level comes from Bureau van Dijk's bankscope dataset. I follow other authors and use the equity ratio banks as a proxy for the bank's weakness (Jiménez et al., 2014; Schivardi et al., 2020; Acharya et al., 2019; Peek and Rosengren, 2005). I define a bank as weak if it was below the median of the distribution of banks' equity ratios in the pre crisis and pre treatment year 2007. 62% of firm-year observations are linked to a weak bank, as reported in Table 10, i.e., weak banks are slightly larger in terms of customer base. I further add firm balance sheet data from Bureau van Dijk's Amadeus database and use the information on the firm-bank link by the Dafne database which also comes from Bureau van Dijk. I can only approximate lending via observable balance sheet positions that I have available from Amadeus. These are total long term debt, which proxies long term bank loans, and short term debt loans, which I assume are short term loans from firm i's only bank. Long term debt encompasses also other obligations than long term bank loans, and hence the effect might be greatly underestimated.

I define a firm as weak if it is highly leveraged following Schivardi et al. (2017). The degree of indebtedness of market participants plays an important role for financial and economic stability and economic development. Highly leveraged firms react more sensitive to decreased demand by reducing their labor force more quickly and thereby contributing to a propagation of adverse shocks Sharpe (1994). They performed worse in and after the great recession in terms of poorer sales growth, investment behavior and employment (Altunok and Oduncu, 2013; Kuchler, 2015; Giroud and Mueller, 2015). According to Traczynski (2017) firm leverage is one of the main explanatory variable for default risk. Cathcart et al. (2018) even claim it is the most important explanatory variable for default risk of SMEs.

In particular, I partition my sample at the sixth, seventh and eight percentile and define a firm as weak if it was at or above the respective decile in terms of mean leverage in the pre period within the sector it operates in. I use the mean over the whole pre period as some firms do not report every year and hence I can obtain the highest coverage of firm year observations.

Identification I estimate the following regression model to test whether banks change their lending behavior as a response to the SMP:

$$
\begin{aligned}
Y_{it} = {} & \alpha_i + \alpha_{rt} + \alpha_{kt} \\
& + \gamma_1 \times \text{SMP}_i \times Post_t \\
& + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{Weak\_bank}_i \\
& + \gamma_3 \times \text{SMP}_i \times Post_t \times \text{Weak\_firm}_i \\
& + \gamma_4 \times \text{SMP}_i \times Post_t \times \text{Weak\_bank}_i \times \text{Weak\_firm}_i \\
& + \cdots + \epsilon_{it}.
\end{aligned}
\tag{6}
$$

As dependent variable I use log changes of long term debt of firm i in year t on firm i's balance sheet. Though SMEs rarely issue long term bonds (Moritz et al., 2016; Demary et al., 2016), they might be financed by long term leasing debt contracts which would also be included in this variable. It is hence far from perfect to capture long term bank debt and can only be interpreted as an approximation. Further, I use and log changes of short term loans as an approximation of short term bank loans to firm i in year t.

SMP is a binary variable and indicates whether firm i is linked to a bank that held SMP eligible assets in 2010, and 0 otherwise. The dummy variable $Post$ equals 0 in the pre period 2007-2009, and 1 in the post period 2010-2013. $Weak\_bank$ and $Weak\_firm$ are defined as described above.

Results might be driven by demand shocks on the regional or industry level, as well as by time invariant unobservables on the firm level. To mitigate these concerns I include an extensive set of fixed effects: Firm fixed effects α_i, bank fixed effects α_b, region-time fixed effects α_{rt}, and industry-time fixed effects α_{kt}. As the treatment variable varies on the bank level I cluster standard errors are on the bank level.

F.1 Tables replication exercise on bank lending

Table 10: Summary Statistics on bank lending

This table reports summary statistics for a sample of 11,809 small and medium sized German firms. Δ *ltdb* is non-current liabilities debt plus 1 in logs (EUR). SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. *Post* equals 0 in pre period 2007-2009 and 1 in period 2010-2013. $Weak\_bank$ is an indicator variable which equals 1 if the bank was below the median capitalization of all banks in year 2007, and 0 otherwise. $Weak\_firm$ in an indicator which equals 1 if firm i is among the highest x decile in terms of mean leverage in the pre period within its sector, and 0 otherwise.

	N	mean	sd	min	p50	max
Δltdb	38,661	-0.288	4.115	-15.171	0.000	14.710
SMP	38,661	0.257	0.437	0.000	0.000	1.000
Post	38,661	0.797	0.402	0.000	1.000	1.000
Weak_bank	38,661	0.620	0.485	0.000	1.000	1.000
Weak_firm: >=6. decile	38,661	0.561	0.496	0.000	1.000	1.000
Weak_firm: >=7. decile	38,661	0.449	0.497	0.000	0.000	1.000
Weak_firm: >=8. decile	38,661	0.329	0.470	0.000	0.000	1.000

Table 11: Heterogeneous lending behavior as a response to the SMP

This table reports results from estimating $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times \text{Weak\_bank}_i \times Post_t + \gamma_3 \times \text{SMP}_i \times \text{Weak\_firm}_i \times Post_t + \gamma_4 \times \text{SMP}_i \times Post_t \times \text{Weak\_bank}_i \times \text{Weak\_firm}_i + \cdots + \epsilon_{it}$. Dependent variable is first differences of log of long term debt. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $Weak\_bank$ is an indicator variable which equals 1 if the bank was below median capitalization of all banks in the year 2007, and 0 otherwise. $Weak\_firm$ is an indicator which equals 1 for high leveraged firms and 0 otherwise. In particular, in column III it equals 1 for firms in upper four, in column IV in upper three and in column V in upper two deciles in terms of leverage of firms in the pre period within sector of firm i. Robust standard errors are clustered on the bank level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV)	(V)
	ΔLtdb	ΔLtdb	ΔLtdb	ΔLtdb	ΔLtdb
Firm leverage deciles			>=6.	>=7.	>=8.
SMP×Post	0.244	0.488	1.503**	1.320**	0.978**
	(0.245)	(0.409)	(0.664)	(0.595)	(0.496)
SMP×Post×Weak_bank		-0.345	-1.305	-1.108	-0.888
		(0.518)	(0.806)	(0.721)	(0.614)
SMP×Post×Weak_firm			-1.870**	-1.805**	-1.537*
			(0.795)	(0.790)	(0.801)
SMP×Post×Weak_bank×Weak_firm			1.759*	1.632*	1.756*
			(0.922)	(0.917)	(0.909)
Observations	38,663	38,663	38,663	38,663	38,663
R-squared	0.286	0.286	0.287	0.287	0.286
Weak_bank×Post	-	Yes	Yes	Yes	Yes
Weak_firm×Post	-	-	Yes	Yes	Yes
Weak_bank× Weak_firm×Post	-	-	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes

Table 12: Variable definitions

Name	Unit	Desciption	Source
Investments	log differences	$investments = log[(fias + 1) + depr]_t - log(fias + 1)_{t-1}$ with fixed assets (fias) and depreciation (depr). Winsorized at the 1 and 99% level by year.	Amadeus
Post	0/1	Equals 0 in pre period 2007-2009, equals 1 in post period 2010-2013.	own calculations
SMP	0/1	Treatment variable equals 1 if firm has link to bank which held SMP eligible assets in 2010 and 0 otherwise.	Koetter (2020)
SMP_precise	0/1	Treatment variable equals 1 if firm has link to bank which held SMP eligible assets in 2010 and 0 otherwise. Defines only firms as treated which are low leveraged (mean leverage ratio in pre period >= eight decile of all firms), or which are high leveraged and linked to a low capitalized bank ($Weak\_bank$).	Koetter (2020)
SMPshare	[0,1]	Share of treated firms within same region–sector cluster in 2010 without firm i.	Koetter (2020), own calculations
SMPshare_precise	[0,1]	Share of treated firms within same region–sector cluster in 2010 without firm i. Includes only firms as treated which are low leveraged (mean leverage ratio in pre period >= eight decile of all firms), or which are high leveraged and linked to a low capitalized bank ($Weak\_bank$).	Koetter (2020), own calculations
SMPshare_IO	[0,1]	Share of treated firms within same input-output clusters and the same region in 2010 according to Kelton et al. (2008) without firm i.	Koetter (2020), own calculations
Non_tradeable	0/1	Equals 1 if firm i operates in industry producing mainly tradeables according to Delgado et al. (2014), and 0 otherwise.	Amadeus
High_tech	0/1	Equals 1 if firm i operates in high-tech industry according to Kile and Phillips (2009), and 0 otherwise.	Amadeus
High_tech_Decker	0/1	Equals 1 if firm i operates in high-tech industry according to Decker et al. (2020), and 0 otherwise.	Amadeus
Δempl	log differences	First differences of log(number of employees). Winsorized at the 1 and 99% level by year.	Amadeus
Δsales	log differences	First differences of log(operational revenue (turnover) + 1). Winsorized at the 1 and 99% level by year.	Amadeus
Δebitda	log differences	First differences of log(earnings before interest, taxes, depreciation and amortization +1). Winsorized at the 1 and 99% level by year.	Amadeus
Δdebt	log differences	First differences of log(current assets debt +1). Winsorized at the 1 and 99% level by year.	Amadeus
Δcash	log differences	First differences of log(cash +1). Winsorized at the 1 and 99% level by year.	Amadeus
market_share	ratio	operational revenue of firm i in year t over total sales of all firms available in Amadeus within same region–sector.	Amadeus, own calculations
Δ loan	log differences	Log of current liabilities loans plus 1. Winsorized at the 1 and 99% level by year.	Amadeus
Δ long term debt	log differences	Log of non-current liabilities long term debt plus 1. Winsorized at the 1 and 99% level by year.	Amadeus
Weak_bank	0/1	Equals 1 if bank of firm i was below median in terms of capitalization in 2007.	Bankscope, own calculations
Weak_firm	0/1	Equals 1 if firm i was euqal or above the sixth, seventh or eigth decile in terms of mean leverage in the pre period.	Amadeus, own calculations

References

Abbassi, P., R. Iyer, J.-L. Peydró, and F. R. Tous (2016). Securities trading by banks and credit supply: Micro-evidence from the crisis. *Journal of Financial Economics 121*(3), 569–594.

Acharya, V. V., T. Eisert, C. Eufinger, and C. Hirsch (2019). Whatever it takes: The real effects of unconventional monetary policy. *The Review of Financial Studies 32*(9), 3366–3411.

Altunok, F. and A. Oduncu (2013). Firm leverage and the financial crisis. *MPRA Working Paper*.

Antoni, M., S. Müller, M. Koetter, and T. Sondershaus (2019). Do asset purchase programs shape industry dynamics? Evidence from the ECB's SMP on plant entries and exits. *IWH Discussion papers No. 12*.

Beck, T., S. Da-Rocha-Lopes, and A. F. Silva (2020). Sharing the pain? credit supply and real effects of bank bail-ins. *The Review of Financial Studies*.

Benoit, J.-P. (1984). Financially constrained entry in a game with incomplete information. *RAND Journal of Economics*, 490–499.

Berg, T., M. Reisinger, and D. Streitz (2021). Spillover effects in empirical corporate finance. *Journal of Financial Economics forthcoming*.

BMWi (2018). "Wirtschaftsmotor Mittelstand Zahlen und Fakten zu den deutschen KMU. 2017 ein erfolgreics Jahr für den Mittelstand.".

Brakman, S., H. Garretsen, J. Gorter, A. van der Horst, and M. Schramm (2005). *New economic geography, empirics, and regional policy.* Number 56. CPB.

Bustamante, M. C. and L. Frésard (2020). Does firm investment respond to peers' investment? *Management Science*.

Caballero, R. J., T. Hoshi, and A. K. Kashyap (2008). Zombie lending and depressed restructuring in Japan. *American Economic Review 98*(5), 1943–77.

Casiraghi, M., E. Gaiotti, M. L. Rodano, and A. Secchi (2016). The impact of unconventional monetary policy on the Italian economy during the sovereign debt crisis. *International Journal of Central Banking 12*(2), 269–315.

Cathcart, L., A. Dufour, and L. Rossi (2018). The Differential Impact of Leverage on the Default Risk of Small and Large Firms. *SSRN*.

Combes, P.-P. and L. Gobillon (2015). The empirics of agglomeration economies. In *Handbook of regional and urban economics*, Volume 5, pp. 247–348. Elsevier.

Cycon, L. and M. Koetter (2015). Monetary policy under the microscope: Intra-bank transmission of asset purchase programs of the ECB. *IWH Discussion Papers No. 9*.

De Pooter, M., R. F. Martin, and S. Pruitt (2018). The liquidity effects of official bond market intervention. *Journal of Financial and Quantitative Analysis*, 1–26.

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2020). Changing business dynamism and productivity: Shocks versus responsiveness. *American Economic Review 110*(12), 3952–90.

Delgado, M., R. Bryden, and S. Zyontz (2014). Categorization of traded and local industries in the US economy. Technical report, Mimeo. Available online at: http://www. clustermapping.us.

Demary, M., J. Hornik, and G. Watfe (2016). Sme financing in the eu: Moving beyond one-size-fits-all. Technical report, IW-Report.

Diamond, D. (2001). Should banks be recapitalized? *FRB Richmond Economic Quarterly 87*(4), 71–96.

Donohoe, M. P., H. Jang, and P. Lisowsky (2018). Competitive externalities of tax cuts. *Available at SSRN 3265532*.

Doran, D., P. Dunne, A. Monks, G. O'Reilly, et al. (2013). Was the Securities Markets Programme effective in stabilizing Irish sovereign yields? *Bank of Ireland Research Technical Paper 7*.

Dougal, C., C. A. Parsons, and S. Titman (2015). Urban vibrancy and corporate growth. *The Journal of Finance 70*(1), 163–210.

Eser, F. and B. Schwaab (2016). Evaluating the impact of unconventional monetary policy measures: Empirical evidence from the ECB's Securities Markets Programme. *Journal of Financial Economics 119*(1), 147–167.

Fracassi, C. (2017). Corporate finance policies and social networks. *Management Science 63*(8), 2420–2438.

Ghysels, E., J. Idier, S. Manganelli, and O. Vergote (2016). A high-frequency assessment of the ECB Securities Markets Programme. *Journal of the European Economic Association 15*(1), 218–243.

Giannetti, M. and A. Simonov (2013). On the real effects of bank bailouts: Micro evidence from Japan. *American Economic Journal: Macroeconomics 5*(1), 135–67.

Gibson, H. D., S. G. Hall, and G. S. Tavlas (2016). The effectiveness of the ECB's asset purchase programs of 2009 to 2012. *Journal of Macroeconomics 47*, 45–57.

Giroud, X. and H. M. Mueller (2015). Firm leverage and unemployment during the great recession. Technical report, National Bureau of Economic Research.

Greenstone, M., R. Hornbeck, and E. Moretti (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of Political Economy 118*(3), 536–598.

Grosse-Rueschkamp, B., S. Steffen, and D. Streitz (2019). A capital structure channel of monetary policy. *Journal of Financial Economics 133*(2), 357–378.

Heckler, D. E. (2005). High-technology employment: a naics-based update. *Monthly Lab. Rev. 128*, 57.

Huber, K. (2018). Disentangling the effects of a banking crisis: evidence from German firms and counties. *American Economic Review 108*(3), 868–98.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina (2014). Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking? *Econometrica 82*(2), 463–505.

Kelton, C. M., M. K. Pasquale, and R. P. Rebelein (2008). Using the north american industry classification system (naics) to identify national industry cluster templates for applied regional analysis. *Regional Studies 42*(3), 305–321.

Keuschnigg, C. and M. Kogler (2020). The Schumpeterian role of banks: Credit reallocation and capital structure. *European Economic Review 121*, 103349.

Kile, C. O. and M. E. Phillips (2009). Using industry classification codes to sample high-technology firms: Analysis and recommendations. *Journal of Accounting, Auditing & Finance 24*(1), 35–58.

Koetter, M. (2020). Lending effects of the ecb's asset purchases. *Journal of Monetary Economics 116*, 39–52.

Kuchler, A. (2015). Firm leverage and investment during the cirsis. Technical report, Danmarks Nationalbank Working Papers.

Lerche, A. (2018). Investment tax credits and the response of firms. *mimeo*.

Moritz, A., J. H. Block, and A. Heinz (2016). Financing patterns of european smes–an empirical taxonomy. *Venture Capital 18*(2), 115–148.

Peek, J. and E. S. Rosengren (2005). Unnatural selection: Perverse incentives and the misallocation of credit in Japan. *American Economic Review 95*(4), 1144–1166.

Schivardi, F., E. Sette, and G. Tabellini (2017). Credit misallocation during the European financial crisis. *BIS Working Papers* (669).

Schivardi, F., E. Sette, and G. Tabellini (2020). Identifying the real effects of zombie lending. *The Review of Corporate Finance Studies 9*(3), 569–592.

Sharpe, S. A. (1994). Financial market imperfections, firm leverage, and the cyclicality of employment. *American Economic Review 84*(4), 1060–1074.

Shleifer, A. and R. W. Vishny (1988). The efficiency of investment in the presence of aggregate demand spillovers. *Journal of Political Economy 96*(6), 1221–1231.

Stolz, S. and M. Wedow (2010). Extraordinary measures in extraordinary times: Public measures in support of the financial sector in the EU and the United States. *Bundesbank Discussion Paper Series* (13).

Traczynski, J. (2017). Firm default prediction: A bayesian model-averaging approach. *Journal of Financial and Quantitative Analysis 52*(3), 1211–1245.