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# Do Asset Purchase Programmes Shape Industry Dynamics? Evidence from the ECB‘s SMP on Plant Entries and Exits*

## Abstract

Asset purchase programmes (APPs) may insulate banks from having to terminate relationships with unproductive customers. Using administrative plant and bank data, we test whether APPs impinge on industry dynamics in terms of plant entry and exit. Plants in Germany connected to banks with access to an APP are approximately 20% less likely to exit. In particular, unproductive plants connected to weak banks with APP access are less likely to close. Aggregate entry and exit rates in regional markets with high APP exposures are also lower. Thus, APPs seem to subdue Schumpeterian cleansing mechanisms, which may hamper factor reallocation and aggregate productivity growth.

*Keywords: plant exit, factor reallocation, asset purchase programmes*

*JEL classification: E58, G21, G28, G33*

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# 1 Motivation

The reallocation of production factors from unproductive to more-productive firms is crucial to maximize aggregate total factor productivity (TFP) growth (Hsieh and Klenow, 2009). Such reallocation implies that more-productive firms become larger (Bartelsman et al., 2013) and that unproductive firms shrink and ultimately exit (Caballero and Hammour, 1994, 1996).

However how much of such a cleansing effect remains after a decade of ultra-loose monetary policy since the Great Financial Crisis of 2007/2008? We empirically test whether and how a heterogeneously transmitted asset purchase policy shock from the European Central Bank (ECB) mutes the factor reallocation mechanism that works in conventional times by forcing the exit of unproductive plants. Dynamic theory models show how micro-founded frictions in labor (Jovanovic, 2014) and financial markets (Moll, 2014) endogenously prevent TFP growth, either through the distortion of market entry or via the misallocation of capital across incumbent firms (Bueara et al., 2011; Restucia and Rogerson, 2017).

This paper empirically isolates a new channel by which asset purchase programs (APPs) may distort factor reallocation: the deterrence of plant exits due to exogenous increases in bank lending capacity. The novel combination of granular plant exit data and individual bank exposures to the Securities Market Program (SMP), the first APP conducted by the ECB between 2010 and 2012, covers the population of banks and a sample of German firms. These comprehensive data allow for the identification of unconventional monetary policy effects on individual plants and when supplemented by 50% of the population of all German plants provide micro-founded evidence on aggregate industry dynamics.

Plants that are connected to banks that benefited from the policy shock exhibit exit rates that are approximately 20% lower than plants connected to banks that were not exposed to the APP. In particular, unproductive firms connected to the least capitalized banks are the least likely to exit. This unhealthy coincidence of bad banks with access to APP helping bad firms to avoid exit is in line with evidence in Jiménez et al. (2014) that a loose (conventional) monetary stance in the Eurozone causally induced weak Spanish banks to inefficiently extend credit to unproductive firms in Spain. Our study complements their finding of inefficiently increasing credit by revealing an undue reduction in necessary churn. Quantitatively, the marginal effect of a weak bank having access to the SMP shock on unproductive plant exit probabilities is a 50 basis-point reduction, which is large in light of average exit rates of 2.6 percentage points during the sample period.

In addition to plant exit rates for a sample with observable traits, we mobilize all ten million plant-year observations for the years 2007-2013 from the Establishment History Panel (BHP, Betriebshistorikpanel) for aggregate analyses at the region and sector levels. These data cover half of the population of plants in Germany. Aggregate entry and exit rates are lower in regions and sectors with higher shares of plants connected to APP-exposed banks. This effect is amplified in unproductive regions, which is consistent with the plant-level evidence that unproductive firms tied to weakly capitalized banks exhibit lower exit rates. Thus, APPs to support stressed Eurozone members generally suppressed industry dynamics in the form of fewer exits and entries. The result that unproductive plants and regions exhibit less churn raises concerns of potential factor misallocation towards unproductive agents in non-stressed Eurozone economies.

Plant-level and aggregate results are based on the combination of administrative data on German corporations, plants, and banks, which is necessary to trace the transmission of the first European APP from the ECB via national (central) banking systems to corporate bank customers and, ultimately, their plants. First, we observe a unique sample from the universe of all plant closures in Germany based on the BHP between 2007 and 2013 (Hethey and Schmieder, 2010), which are linked to firm identities. Second, we observe transaction data from the ECB during the SMP at the security level. The SMP stabilized asset prices (Eser and Schwaab, 2016), caused increases in credit supply (Koetter et al., 2017), and stimulated the macroeconomy (Gibson et al., 2016). The causal effects on plant entries and exits, and thus industry dynamics, remain unclear. Third, we identify banks that are exposed to the unexpected regime change by the ECB in the form of the SMP via the security holdings statistics of the German central bank as in Koetter et al. (2017). Finally, we match firm identities to all banks – exposed and unexposed – based on bank-firm relationships reported in the Amadeus database. To the best of our knowledge, we are the first to study such a granular chain from the financial to the real sector of a large, developed economy with respect to the implications of APPs for cleansing effects as reflected by the forced attrition of unproductive plants.

This exercise complements theoretical advances by Osotimehin and Pappadá (2017). They model the relationship between (voluntary and forced) firm exits, financial constraints, and aggregate productivity. Credit constraints alter the cleansing mechanism such that a fraction of very productive firms is forced to leave the market. Some unproductive firms remain because exit choices also depend on the expected net worth of firms. Our paper fills the gap in the empirical literature and tests these theoretical implications.

Whereas plant exits are hardly studied, a large body of research investigates how financial frictions affect the entry of young firms and resulting industry dynamics. For example, Cetorelli and Strahan (2006) show that lackluster banking market competition deters new entrants in U.S. markets. In a related work, Kerr and Nanda (2010) show the branch deregulation in the U.S. enhanced competition, which causally increased entry rates of firms without necessarily increasing the size of these entrants.They conclude that the elimination of financial frictions in banking affects real economic activity, particularly via the birth of new firms. These studies focus on the provision of financial funds to incumbent firms or the entry of new entrants. However, they neglect the effect of changes to financial frictions on the exit of unproductive units, which is key for the reallocation of production factors. One of the few studies that also considers the exit of unproductive corporations – but not plants – is Kerr and Nanda (2009). They report that U.S. banking market deregulation increased not only market entry but also exit rates.

Regarding empirical evidence for Europe, the lack of homogenous administrative data and the limited number of publicly listed firms pose severe hurdles to the availability of comparable data on market exits. An exception is Bertrand et al. (2007), who demonstrate that the deregulation of French banking markets also reduced the bailout of unproductive corporations by the financial sector and that industries with greater exposure to more competitive banking markets exhibit faster factor reallocation. However, this important finding of less frequent bailouts of unproductive firms via their banks is not obtained through the direct observation of exits; rather, the authors infer inefficient lending from below-equilibrium lending conditions (see also Caballero et al., 2008, on the phenomenon of "zombie" firms). We, in turn, observe plant exits, the productive units of physical activity, in contrast to inferring churn based on financial data at the firm level.

Empirical evidence at the plant level regarding the aggregate productivity effects of financial frictions is generally scarce, but it is crucial to the understanding of aggregate phenomena. Hsieh and Klenow (2014) use plant-level data to estimate that aggregate manufacturing productivity in Mexico and India lags behind that of the U.S. by one quarter due to insufficient investment in process efficiency and product quality. They remain agnostic about the sources of under-investment, but financial frictions may well play a role.

The effect of such frictions on aggregate productivity via distortions at the plant level is little documented. Midrigan and Xu (2014) exploit establishment data from South Korea, Colombia, and China to separate entry distortions from capital misallocation among existing plants due to financial frictions. However, they speak neither to heterogeneous policy effects nor to the role of delaying the attrition of unproductive plants, which is our focus.

Related to our work, Gopinath et al. (2017) demonstrate that the dispersion of capital returns across Spanish (and, further, Southern European) manufacturing firms increased between 1999 and 2012. Declining real interest rates due to European financial integration during this time caused the misallocation of abundantly inflowing capital that was directed towards overly unproductive firms, ultimately reducing TFP. Their study of the effects of a policy shock to the supply of financial funds provides important evidence on the intensive margin of misallocation. We complement this important evidence with insights on the extensive margin of misallocation, i.e., the delay-of-exit effect due to the loose supply of financial funds. Whereas they model financial frictions as depending on firm size, we directly observe the exposure of plants to loose monetary policy shocks via bank-firm relationships. In addition, we observe small and medium-sized enterprises (SMEs) for which market exit is more likely in general (Fackler et al., 2013) and driven by competitive reallocation forces in particular (e.g., Dosi et al., 2015).

# 2 Data

## 2.1 Monetary policy and bank data

The impact of the SMP program on German plants is an ideal testing ground to isolate the causal impact of APPs on industry dynamics. In response to soaring risk premiums in May 2010, the ECB purchased sovereign bonds of Greece, Ireland and Portugal. It extended its purchases to Italian and Spanish bonds in August 2011. By September 2012, the ECB had purchased a notional volume of EUR 218 billion. Whereas the size of the SMP is small compared to subsequent APPs, the ECB's actions were in contrast to those of the U.S. Federal Reserve, which had been extremely reluctant to intervene in securities markets. The beginning of the SMP thus marked an unexpected regime shift to the reduce risk premia of the sovereign bonds of crisis countries and was a response to neither stressed firms nor troubled banks in Germany. This policy shock helps to isolate whether APPs had unintended effects on firms in non-stressed Eurozone countries.

Following Koetter et al. (2017), we match ISIN codes from the ECB's purchase schedule to the security holdings reported by all German banks to the central bank to identify banks that hold eligible SMP assets. Exposures to SMP securities increase excess reserves and associated credit-generating capacity either through an unloading channel, if assets are sold to the ECB, or through a valuation channel, if they are retained but revalued at higher market prices (Eser and Schwaab, 2016).

To limit concerns about confounding policies, we focus in our plant-level analysis on regional savings and cooperative banks that hold sovereign debt primarily as a store of liquidity given its regulatory treatment as a risk-free asset. Sovereign debt holdings from the EU periphery, which were purchased under the SMP, were pervasive: two-thirds of banks, including very small ones, had such exposure to the EU periphery (Buch et al., 2016). Large German banks, in turn, engaged much more actively in (proprietary) securities trading and were subject to many confounding policy events, such as changes to the collateral framework, long-term refinancing operations, or even foreign policy measures that affected them via their cross-border activities (Buch et al., 2019). Excluding these large financial institutions mitigates the possibility that banks in our sample purposefully accumulated Southern European bonds in anticipation of some form of rescue plan from the ECB or the EU. Moreover, the German economy is particularly useful to study regional responses of industry dynamics to APPs because the local banks investigated here operate only in regional markets that largely coincide with county borders (German Council of Economic Experts, 2013). Local savings and cooperative banks are the relationship bankers of SMEs and, as such, are crucial for the transmission and mitigation of both shocks and policy (Koetter et al., 2019). We add financial account data from the Bankscope database to gauge banks' financial strength.

## 2.2 Firm and plant data

To identify the effect of the SMP on the real economy through plant exits, we link banks to non-financial corporations using Bureau van Dijk's (BvD) Amadeus database. It contains financial information at the firm level for 6,332,435 firm-year observations in our sample period from 2007 until 2013. Similar to Kalemli-Özcan et al. (2015), Kalemli-Özcan et al. (2016), Popov and Rocholl (2018), or Huber (2018), we obtain bank-firm links from BvD's Dafne database.[1] To isolate the effect of the SMP shock, we only sample

[1] We extrapolate missing firm-bank links in early years using 2010 as a base year.

firms with a single bank relationship. Consequently, the sample comprises many SMEs – with a mean (median) number of employees of 11 (4) – which cannot substitute their non-treated bank with a link to a treated bank.

However, neither Amadeus nor Dafne contains information on the production plants of these firms. In fact, few studies shed light on the production sites of such SMEs, which in turn account for a large share of GDP in many developed economies. Therefore, we combine firm identifiers and traits with the BHP (Schmucker et al., 2016) provided by the Institute for Employment Research (IAB, Institut für Arbeitsmarkt und Berufsforschung, Nürnberg) as in Schild (2016) and Antoni et al. (2018). The BHP aggregates worker-level social security notifications at the plant level and covers 50% of the German plant population. This dataset provides us with information on the workforce composition of plants and the employees' wages. We follow Hethey and Schmieder (2010) and use worker flows to identify plant exits.

– Table 1 around here –

Table 1 summarizes the variables from plants and banks at the plant-year level: plant exits and observable traits as well as bank financials. In addition, we report summary statistics on bank and firm weakness indicators, as well as regional and sector aggregates. Table A.1 in the Appendix provides the definition and source of each variable.

The merged dataset contains 2,560,878 plant-year observations that are operated by firms linked to one regional savings or cooperative bank. In addition, we condition on firm existence since 2006 and exclude firms from the forestry, agricultural, and financial sectors. The resulting sample comprises 593,357 German plant-year observations corresponding to approximately 85,000 plants per year between 2007 and 2013. All subsequent estimations use the most restrictive sample, in which we observe all indicators to distinguish between weak and strong banks and productive and unproductive plants. This final sample comprises 28,144 firms with 31,877 plants, or 202,386 plant-year observations.

Of the firms in our sample, 96.8 % are single-plant firms. The median plant employs four full-time-equivalent employees and is thus very small. This feature reflects the fact that our firms are mainly SMEs, which are more substantially affected by financial frictions than are large, listed multinationals. In Germany, 47% (66%) of plants have fewer than 5 (10) full-time-equivalent employees, and the vast majority of all firms are single-plant firms (Koch and Krenz, 2010). Hence, this sample of small firms mimics the population very well. We define a bank as treated if it held an SMP asset in all three SMP years, 2010-2012. According to this definition, 11.6% of all observations or 10.7% of all plants are treated. Because we estimate difference-in-differences models to isolate the effect of the SMP on industry dynamics, we test whether these two groups of plants are comparable by means of t-tests on selected variables at the plant and bank levels.

– Table 2 around here –

Table 2 reports differences in levels across treated and non-treated observations for the pre and post period, respectively, as well as the corresponding difference-in-differences term. Both non-treated and treated plants show an average exit probability of 1.1% in the pre period. The exit rate for both groups increases in the post period, albeit more so for the non-treated group. As such, any potential effect of unconventional monetary policy that blocks the exit of firms tied to banks with additional credit-bearing capacity is not obviously visible from this non-parametric, unconditional comparison. Treated plants are larger than non-treated plants in terms of average number of employees (10.5 versus 14.3) and are slightly older (13.8 versus 14.2 years). Treated banks have slightly lower equity ratios and a lower return on assets, and while they are statistically significantly larger in size, this difference is economically negligible.

– Table 3 around here –

Treated and non-treated plants may differ in terms of covariate levels but must exhibit identical trends prior to treatment. Table 3 reports t-tests for changes in the respective variables. None of the plant, firm, or bank traits differ. The treatment and control groups exhibit parallel trends in observables prior to the SMP, and we employ a difference-in-differences approach.

# 3 SMP effects on plant exit

## 3.1 Headline results

To quantify the effect of the SMP on plant closures, we use a difference-in-differences model to compare exits before and after the launch of the APP between plants with and without ties to SMP banks:

$$Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma SMP_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}. \tag{1}$$

The dependent variable $Exit_{it}$ is an indicator equal to 1 in year $t$ when plant $i$ exits. Plant fixed effects $\alpha_i$ gauge unobservable heterogeneity.[2] We also specify region-time fixed effects $\alpha_{rt}$ and sector-time fixed effects $\alpha_{kt}$.

The variable $SMP_i$ equals 1 if plant $i$ is linked to a bank that held SMP-eligible assets in all three treatment years. $Post_t$ equals 1 in the period 2010-2013 after the SMP commenced. We estimate the model for the full sample with lagged bank-level controls and the second, third and fourth polynomial of firm age ($X_{it-1}$).[3] We cluster standard errors at the level of treatment, which is the bank level. Table 4 presents the headline results.

– Insert Table 4 around here –

The parsimonious specification in column I of Table 4 includes, in addition to plant and time fixed effects, only higher order polynomials of plant age as a control variable. The coefficient of interest is the interaction term, which is significant at the 10% confidence level and negative. The magnitude of -0.3 percentage points is economically meaningful, as average exit rates are on the order of 2.3 percentage points.

[2]As most plants are operated by single-plant firms (96.8%), this fixed effect almost perfectly absorbs unobserved firm heterogeneity.

[3]Bank controls are defined in Table A.1 and follow the C(apitalization), A(sset quality), M(anagement skill), E(arnings), L(iquidity) taxonomy used, for example, by U.S. regulators to generate micro-prudential ratings of banks, plus bank size.

Irrespective of exposure to the SMP, plant exits may also depend on differences in bank health. Therefore, we add in column II bank-specific CAMEL covariates plus bank size to gauge financial profiles. The differential effect of the SMP on plant exits increases in size and is now statistically significant at the 5% level. Columns III and IV further scrutinize reduced plant exit rates due to the SMP by controlling for region-time and sector-time fixed effects. Controlling for unobservable shocks in regions or sectors entails an even larger, negative differential effect of the SMP on plant exits.

The magnitude of a reduction in mean exit rates by 0.5 percentage points is confirmed in the most conservative specification in column V, where we jointly control for all three types of fixed effects. Plants that are connected to firms with access to the SMP are almost 22% less likely to exit after the SMP started than plants without access to this APP.

Whereas this specification with many fixed effects should mitigate concerns of potentially confounding shocks, it remains important to ensure that it is indeed the SMP shock to which plant exit rates respond. To this end, we randomly assign placebo exposures to the SMP across plants that mimic the moments of the observed treatment distribution in the sample across plants and re-estimate the difference-in-differences model in Equation (1).

– Insert Table 5 around here –

Column I in Table 5 reports the results for a placebo treatment that is assigned randomly across plants according to the overall treatment share. Column II shows the results for a placebo treatment that is assigned randomly for each year across plants according to the treatment share per year. Column III reports the results for a placebo treatment that is assigned randomly across plants and years. All three placebo estimations yield no significant results.

## 3.2 Channels

The finding that the SMP suppressed plant closures (which serve as an important cleansing mechanism) is consistent with other evidence that the provision of emergency liquidity to banks induces lending to unproductive firms that should have exited (Caballero et al., 2008). Similarly, Jiménez et al. (2014) demonstrate that loose (conventional) European monetary policy contributed to the accumulation of credit risks in the Spanish financial system by misallocating credit via poorly capitalized banks to the least productive firms.

To test for such possible channels for adverse effects, we interact the baseline specification with indicators of weak banks and weak firms in Equation (2):

$$Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}. \quad (2)$$

$WB_i$ is an indicator equal to 1 if the bank was in the lowest quartile of the capitalization distribution in 2007, which corresponds to an equity ratio below 5.56%. Analogously, $WF_i$ is an indicator equal to 1 if the plant was in the lowest quartile of the productivity distribution in its sector before the SMP was launched. Banks' capitalization ratios equal equity over total assets. Productivity is measured as turnover per employee in each of the 66 sectors in our sample. The variable turnover is only available at the firm level from Amadeus; hence, $WF_i$ is the same within firms across plants. This quadruple difference-in-differences term gauges the effect of a weak bank being exposed to the policy shock on exit rates of plants of unproductive firms relative to the pre-SMP period. Standard errors are again clustered at the level of treatment, i.e., the bank. Table 6 reports marginal effects, which are derived from regression results shown in Table A.2 in the Appendix. For comparison, column I in Table 6 reproduces the headline results of Table 4.

– Insert Table 6 around here –

First, consider the marginal effects of a triple interaction, including a weak bank indicator in column II. Marginal effects are calculated separately for weak and strong SMP banks in the post-APP period. These results corroborate the general insight that plants are less likely to shut down if they are connected to SMP-supported banks. An important qualification here is that only the connection to the least capitalized banks entails a statistically significant reduction of exit probabilities. The economic magnitude of this effect increases drastically. Plants connected to weak SMP banks are on average 0.8 percentage points less likely to exit than non-treated plants. Thus, the transmission of emergency liquidity via weak banks is not a phenomenon confined to stressed Eurozone economies. Unconventional monetary policy also has the undesirable side-effect that weaker intermediaries obtain the means to extend additional credit in stable economies such as Germany.

Column III specifies another indicator for weak firms, and we estimate marginal effects for each of the resulting four strata of weak/strong banks connected to unproductive/productive plants. Plants connected to well-capitalized banks do not exhibit changes in their exit probability, irrespective of their productivity. This result suggests that concerns about undesirable factor misallocation due to unconventional expansionary policy are less prevalent if banking systems are financially stable; see also Gopinath et al. (2017).

In contrast, plants connected to weak banks exhibit significantly lower exit probabilities. The marginal effect for productive firms connected to weak banks is 0.8 percentage points, whereas it equals 1 percentage point for unproductive plants. Both differential effects represent a large reduction relative to the average exit rate of 2.3 percentage points. The numerically small difference between the effects for strong and weak plants might suggest that productivity differentials are not particularly relevant in the transmission of APP shocks. This is not the case. The group of productive firms includes all firms above the $25^{th}$ percentile, which still includes some fairly weak firms.

In general, the unholy combination of weak firms and weak banks drives the misallocation of resources in the form of unrealized plant exits. In Figures 1 and 2, we consider the entire range of thresholds to define weak financial profiles and unproductive plants, respectively.

– Insert Figure 1 around here –

First, we hold the threshold for the weak firm indicator constant and vary the threshold for weak banks across the entire distribution. Figure 1 shows the marginal effect and confidence bands at the 5% level of the treatment for unproductive plants connected to weak banks in the post period varying over different thresholds for the weak bank indicator. A bank is defined as weak if it is below the percentile threshold indicated on the horizontal axis. We depict point estimates of the marginal effects for re-estimations across the distribution of capitalization in one-percentile increments. The effect of the SMP in reducing the exit probabilities of unproductive firms prevails when defining weak banks as those that range approximately between the $5^{th}$ and the $30^{th}$ percentile. Thus, the main results reported for a threshold at the $25^{th}$ percentile are robust.

– Insert Figure 2 around here –

Second, we show marginal effects of the treatment for plants connected to weak banks for different firm productivity thresholds. In Figure 2, the threshold for the weak bank indicator is held constant, and we depict marginal effects and confidence bands at the 5% level across the distribution of productivity thresholds defined at different percentiles. In contrast to the bank stress threshold, the exit-dampening effect of the SMP prevails for a wide range of thresholds from the $15^{th}$ up and until the $60^{th}$ percentile. Hence, not only the very unproductive but also firms with moderate productivity are shielded from forced attrition due to harder-nosed monitoring styles by better capitalized SMP banks.

Overall, the evidence complements earlier studies on the zombification of firms due to overly loose monetary policy because of weak banking systems.

We contribute to this literature by showing that not only is credit misallocated but also the elimination of unproductive plants is subdued. This deactivation of Schumpeterian industry dynamics might entail an even larger misallocation of real resources.

# 4 Regional and sector dynamics

The reduced average exit rates due to the SMP documented thus far may also be accompanied by more credit being available to new entrants that receive funding under a looser monetary policy stance. Because new entrants, by definition, do not yet report an existing bank relationship, we cannot test this hypothesis using plant-level data. Therefore, we next consider whether aggregate industry dynamics – entry and exit rates per region and sector – differ significantly conditional on the share of SMP exposed banks.

## 4.1 Aggregation of microdata

We do so by mobilizing all 10,085,408 plant-year observations in the entire BHP during the years 2007-2013 to estimate the aggregate effects of the SMP on industry dynamics. The exposure of counties or sectors to the SMP shock is gauged by the share of SMP-affected plants $SMPshare$ per county or sector. We use the entire sample of banks, including commercial banks, and obtain the share of treated plants from our matched bank-firm-plant dataset. We extrapolate the total share of treated plants to the region or sector level. Figure 3 depicts the number of incumbent plants (stock), the number of entering firms (entries), and the number of exiting firms (exits) per year by regions above and below the median of their share of SMP-exposed plants.

– Insert Figure 3 around here –

Entry and exit dynamics do not differ visibly between exposed and unexposed counties before and after the SMP shock. To reveal possibly less-obvious changes in aggregate entries and exits, we apply difference-in-differences regressions at the aggregate level. To account for the feature that SMP-exposed regions host more incumbent plants, we specify region fixed effects.

First, we calculate for each of the 402 German counties ("Kreise") average plant entry and exit rates. In addition to regional aggregates, we calculate entry and exit rates by sector to test whether entry and exit rates differ systematically across sectors conditional on greater exposure to the SMP. Table O.1 in the Online Appendix reports sectors according to the 2-digit NAICS, a description of the sector, the SMP share and the number of plants per sector as of 2009. A lower cost of external funding may affect industry dynamics more in sectors with technologies that rely more heavily on capital as a production factor than in sectors that are less exposed to this change in relative factor prices. Table 7 presents tests of the parallel trends assumption at the aggregate level.

– Insert Table 7 around here –

We compare year-on-year changes in the dependent and control variables between 2007 and 2009. T-tests clearly reject that aggregate entry and exit rates differ significantly at the region and the sector level prior to the launch of the SMP. The same holds for most region and sector controls, except for the average change in the number of plants per region and, especially, sector.

## 4.2 SMP effects across regions and sectors

To estimate the changes in aggregate entry and exit rates in response to the policy shock, we gauge the SMP exposure of regions and sectors by the respective share of treated plants in the 402 regions and 66 sectors, respectively, and specify:

$$Y_{rt} = \alpha_r + \alpha_t + \gamma SMPshare_r \times Post_t + \epsilon_{rt}. \tag{3}$$

The dependent variable is the mean entry or exit rate in region $r$ (or sector $k$). We extrapolate the share of treated plants per region $SMPshare_r$ (sector $SMPshare_k$) from the granular sample of firms that includes relationships to all banks. The share of treated plants per region (sector) is interacted with an indicator $Post_t$ that equals 0 for the pre period, 2007-2009, and 1 for the post period, 2010-2013. We include region (sector) fixed effects and time fixed effects and cluster standard errors at the region (sector) level.

– Insert Table 8 around here –

Columns I and II of Table 8 report results at the regional level. Firm entry rates after the launch of the SMP are significantly lower in counties with larger shares of SMP-exposed plants than in the three years preceding this policy shock. The economic impact depends on the $SMPshare$, which equals 42% in the average county. The point estimates imply a reduced entry rate of 0.418 $\times$ (-0.007), or 0.29 percentage points. Against the backdrop of average entry rates on the order of 5 percentage points, this implies a substantial reduction of 5.8%. Expansionary policy shocks in the form of APP not only depress average (unproductive) plant exit rates but also block the entry of new competitors. In the vein of Cetorelli and Strahan (2006), these results may indicate that an erosion of competitive pressure due to APP support for (weak) banks has detrimental effects on the real economy. Lower refinancing costs for banks due to the APP may induce them to prefer the provision of credit to incumbent, possibly less productive customers rather than lending to new, more innovative, but also more costly to screen entrants as in Cetorelli and Gambera (2001).

Column II reports the impact of the share of treated plants in the region on average exit rates. In line with the plant-level results, aggregate regional plant attrition also declines by 0.17 percentage points more in regions exhibiting the mean share of SMP-exposed plants. This estimate corresponds to a contraction of average exit rates of 3% given a mean attrition of 5.5 percentage points. Thus, having a larger share of regional SMP exposure has economically substantial restrictive effects on industrial dynamics.

Columns III and IV report aggregate results at the sector level. Qualitatively, the effect of relatively more SMP-exposed plants on sectoral entry and exit rates mimic the effects at the regional level. However, the effect on subdued entry rates is no longer significant, possibly reflecting the substantially lower number of observations. Therefore, the almost seven-fold estimate of the economic magnitude for the effect of the SMP share on sectoral plant attrition rates should be interpreted with caution.

Note that in contrast to the plant-level exercise in which multiple plants from diverse sectors are nested within each county, we cannot saturate the aggregate regional analyses with an equally tight grid of fixed effects to control for unobservables. In the regional analysis, for example, we account for a federal business cycle and for time-invariant traits of regions but not for systematic differences for each county over time. To challenge the assumption that a difference-in-differences approach at the aggregate level is valid beyond the tests of the parallel trends assumption shown in Table 7, we therefore estimate leads and lags models in the vein of Gormley and Matsa (2016). Specifically, we interact the share or treated plants, $SMPshare_r$, with indicator variables for the years 2007-2013, excluding the immediate pre-treatment year 2009:

$$Y_{rt} = \alpha_r + \alpha_t + \sum_{t=2007,\, t\neq 2009}^{2013} \gamma_t \, D_t \times SMPshare_k + \cdots + \epsilon_{rt}. \tag{4}$$

$D_t$ are year indicators, and $SMPshare$ is the share of treated plants per region or sector. Columns I and II in Appendix Table A.3 report the results at the regional level, while columns III and IV report those at the sector level. The effects of lower entry and lower exit rates are virtually all concentrated in the years after the SMP commenced, thereby confirming the parallel trends assumption.[4]

[4] Only regional entry rates differ in the pre-period year 2007.

The aggregate analysis may also suffer more from potential bias than the plant-level results due to the presence of financial centers in selected counties. Hosts of financial centers may benefit over-proportionally from APP and experience specific economic conditions tied to the financial industry. Therefore, we re-estimate Equation (3) and exclude the local financial centers of Hamburg, Frankfurt (Main), München, Düsseldorf, and Stuttgart from the regional analysis. In the sector-level estimations, we exclude plants from these regions before aggregating plant observations. Tables O.2 through O.5 in the Online Appendix confirm that entry and exit rates at the regional and sectoral levels are each unaffected by this approach.

In sum, the evidence highlights quite clear adverse effects of APP in terms of industry dynamics and thus factor reallocation: (unproductive) firms connected to weak banks survive, new competitors cannot enter the market, and turnover rates decrease.

## 4.3 Heterogenous aggregate transmission

The impact of the SMP on industry dynamics likely depends on the plant population within regions and sectors. Counties that host fewer but relatively many large plants may exhibit even stronger declines in (unproductive) plant attrition if additional bank funding made available by APPs is routed to these fewer customers by banks exposed to the program. Analogously, regions and sectors characterized by relatively low productivity at the time of the shock may suffer even more from suspended innovative renewal because SMP banks may seek to protect their incumbent customers.

To test whether and how regional and sectoral differences affect the transmission of the SMP to aggregate entry and exit, we augment Equation (3) with additional indicators that gauge differences in the respective plant population:

$$Y_{rt} = \alpha_r + \alpha_t + \gamma SMPshare_r \times Post_t \times Indicator_r + \cdots + \epsilon_{rt}. \quad (5)$$

The binary variable $Indicator_r$ captures whether region or sector $r$ is above the mean average plant size or below the mean of two labor productivity measures in the pre period across regions or sectors described below.

– Insert Table 9 around here –

At the regional level, columns I-III of Table 9 report the results when entry rates are the dependent variable. Columns IV-VI present the results when exit rates are the dependent variable. We find no evidence of significantly different entry rates due to asset purchases between regions with large or small plants. Reduced exit rates are entirely driven by regions with large plants. Large plants can make use of liquidity injected into the economy by asset purchases and cause lower exit rates at the aggregate level. Lower exit rates driven by regions with large plants drag more heavily on renewal dynamics than would be the case if they were driven by small plants.

In columns II and V, $Indicator_r$ equals one if mean labor productivity, measured according to the turnover per employee, is below the mean of all regions. As turnover is not available for all plants, the variable is extrapolated from firm information available from Amadeus. We find that lower entry rates and lower exit rates are driven by regions that show low productivity. Regions that are in need of innovation due to their low productivity exhibit even lower renewal rates after they benefited from asset purchases. Column III confirms this result, where $Indicator_r$ also measures labor productivity and equals one if average wage per full-time equivalent is below the mean of all regions. Equivalently, entry rates are driven by regions with low labor productivity. These results match the preceding plant-level analysis. In the granular estimations, we find that weak plants connected to weak banks are the main driver of lower productivity differentials among plants. This is reflected in the estimations at the aggregate level, where low-productivity regions show lower churn rates. Nevertheless, when we use wage as a productivity measure, we do not find a difference between low- and high-productivity regions; both show lower exit rates; see column VI.

– Insert Table 10 around here –

Table 10 reports results for observations aggregated at the sector level. As before, we do not find effects for entry rates. Columns IV-VI show the results on exit rates. Similar to estimations at the region level, we find that sectors with large plants drive the result of lowered exit rates. Large plants benefit from asset purchases and remain in the market. The potential for adverse effects due to reduced Schumpeterian destruction is therefore large. Columns V and VI show the results for productivity measures. At the sector level, we find that high- and low-productivity sectors show reduced exit rates when plants are treated by the SMP. But in contrast to the regional level, it is not the low-productivity sectors that are primarily responsible for the results.

## 5 Conclusion

Between May 2010 and September 2012, the European Central Bank (ECB) launched its first asset purchase program and absorbed sovereign debt from stressed Eurozone economies in secondary markets under the securities markets program (SMP). Based on a unique combination of granular data on plant exits and equally granular data on financial firms and security transactions between 2007 and 2013, we trace this shock and show that the SMP dampened industry dynamics in a large Eurozone economy that was not targeted by this unconventional policy tool: Germany.

Dfference-in-differences analyses at the plant level clearly show that exit probabilities for plants connected to banks that have access to additional APP liquidity decrease. These reduced exit rates are attributable to unproductive firms that are connected to weakly capitalized banks, which is robust to the use of a wide range of thresholds to define weak banks and firms. This result corroborates earlier evidence on the misallocation of credit to so-called zombie firms when monetary policy is overly loose or when governance and market discipline exert too little pressure on banks to enforce weak firm restructuring.

We also assess aggregate industry dynamics in regional markets and 66 two-digit sectors of the German economy. This aggregate perspective exploits more than 10 million plant-year observations and permits analyses of average entry and exit activities in regions and sectors. Both average entry and exit rates are significantly lower in regions that host more banks that are exposed to the SMP shock. This result is qualitatively confirmed at the sector level. The results are driven by regions and sectors with large plants, which underlines the importance for the aggregate economy. Reflecting firm-level analyses, we further find that low-productivity regions, which should be the ones with the largest need and potential for innovative renewal, are the main drivers of the reduction in entries and exits.

Our evidence thus indicates that one economic cost imposed by asset purchase programs is to subdue the factor reallocation facilitated by financial institutions, namely, the exit of unproductive plants and the entry of new competitors.

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# 6 Tables

Table 1: Summary statistics

This table reports summary statistics for 28,144 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. Variables on the plant level are the following: $Exit$ is an indicator that equals 1 if plant $i$ exits in year $t$, $Age$ reports plant age in years, and $Number\ FTE$ is the number of employees in full-time equivalents. Variables on the bank level are the following: *Equity* is the share of equity over total assets (in %), $Cost-to-income$ is the cost to income ratio (in %), $Return\ on\ assets$ is the return on total assets (in %), and *Liquidity* is the share of liquid assets over total assets (in %). All bank-level variables are winsorized at the top and bottom 1% percentile. Furthermore, $Assets$ is the log of total assets (in million EUR). Total assets is winsorized before taking logs at the top and bottom 1% percentile. We use the following indicator variables: $SMP$ equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets. $WB$ is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of equity ratio in the year 2007. $WF$ is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in the year 2007. *Post* equals 0 in 2007-2009 and 1 in 2010-2013. Variables at the regional and sector levels are as follows: $SMPshare$ is the share of treated plants in a region or sector. $Entry\ rate$ is the mean entry rate of plants per region or sector, and $Exit\ rate$ is the mean exit rate of plants per region or sector.

| | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| *Plant* | | | | | |
| Exit | 202,386 | 0.023 | 0.150 | 0.000 | 1.000 |
| Age | 202,386 | 15.825 | 10.023 | 1.000 | 38.000 |
| Number FTE | 202,386 | 11.441 | 52.794 | 0.000 | 9911.000 |
| *Bank* | | | | | |
| Assets | 202,386 | 7.954 | 1.327 | 5.142 | 12.470 |
| Equity | 202,386 | 6.656 | 1.795 | 2.538 | 12.331 |
| Cost-to-income | 202,369 | 69.296 | 10.027 | 44.640 | 145.120 |
| Return on assets | 202,384 | 0.199 | 0.155 | -1.310 | 0.880 |
| Liquidity | 202,386 | 13.617 | 8.656 | 2.144 | 66.974 |
| *Indicators* | | | | | |
| SMP | 202,386 | 0.116 | 0.320 | 0.000 | 1.000 |
| WF | 202,386 | 0.243 | 0.429 | 0.000 | 1.000 |
| WB | 202,386 | 0.383 | 0.486 | 0.000 | 1.000 |
| Post | 202,386 | 0.548 | 0.498 | 0.000 | 1.000 |
| *Region* | | | | | |
| SMPshare | 2,814 | 0.418 | 0.188 | 0.100 | 0.921 |
| Entry rate | 2,814 | 0.050 | 0.010 | 0.024 | 0.088 |
| Exit rate | 2,814 | 0.055 | 0.009 | 0.029 | 0.100 |
| *Sector* | | | | | |
| SMPshare | 462 | 0.476 | 0.106 | 0.212 | 0.805 |
| Entry rate | 462 | 0.055 | 0.030 | 0.000 | 0.253 |
| Exit rate | 462 | 0.055 | 0.028 | 0.000 | 0.154 |

Table 2: T-tests on levels

This table reports the results of t-tests on mean levels of plant- and bank-level variables in the pre and post periods between treated and control groups. The last two columns report the difference-in-differences tests between the means of the two groups over both periods. The sample covers the years 2007-2009 in the pre period and 2010-2013 in the post period. The table reports tests on the following plant-level variables: *Exit* is an indicator that equals 1 if plant $i$ exits in year $t$, $Number\ FTE$ is the number of employees in full-time equivalents, and *Age* reports plant age in years. Tests on the following bank-level variables are reported: *Equity* is the share of equity over total assets (in %), $Cost-to-income$ is the cost to income ratio (in %), $Return\ on\ assets$ is the return on total assets (in %), and *Liquidity* is the share of liquid assets over total assets (in %). All bank-level variables are winsorized at the top and bottom 1% percentile. Furthermore, *Assets* is the log of total assets (in million EUR). Total assets is winsorized before taking logs at the top and bottom 1% percentile. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | | Pre period | | | | Post period | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **LEVELS** | N | Non-treated | Treated | Diff | SE | Non-treated | Treated | Diff | SE | DiD | SE |
| *Plant* | | | | | | | | | | | |
| Exit | 202,386 | 0.011 | 0.011 | 0.000 | 0.002 | 0.033 | 0.031 | -0.002 | 0.001 | -0.002 | 0.002 |
| Number FTE | 202,386 | 10.511 | 14.318 | 3.808*** | 0.545 | 11.310 | 15.940 | 4.63*** | 0.495 | 0.822 | 0.737 |
| Age | 202,386 | 13.825 | 14.198 | 0.373*** | 0.102 | 17.377 | 17.940 | 0.563*** | 0.093 | 0.190 | 0.138 |
| *Bank* | | | | | | | | | | | |
| Equity | 6,265 | 6.382 | 5.939 | -0.443*** | 0.129 | 7.771 | 7.481 | -0.289** | 0.113 | 0.154 | 0.172 |
| Cost-to-income | 6,263 | 71.954 | 72.058 | 0.104 | 0.617 | 67.251 | 66.893 | -0.357 | 0.617 | -0.431 | 0.820 |
| Return on assets | 6,264 | 0.233 | 0.193 | -0.039*** | 0.013 | 0.286 | 0.249 | -0.038*** | 0.011 | 0.001 | 0.017 |
| Liquidity | 6,265 | 15.520 | 15.815 | 0.294 | 0.560 | 12.253 | 13.129 | 0.877* | 0.489 | 0.582 | 0.743 |
| Assets | 6,265 | 6.414 | 6.718 | 0.304*** | 0.083 | 6.517 | 6.797 | 0.280*** | 0.073 | -0.024 | 0.111 |

## Table 3: T-tests on changes

This table reports the results of t-tests on year-to-year changes in plant- and bank-level variables in the pre and post periods between treated and control groups. The last two columns report the difference-in-differences tests between the means of the two groups over both periods. The sample covers the years 2007-2009 in the pre period and 2010-2013 in the post period. For first differences in year 2007, observations from 2006 are also considered. The table reports tests on the plant-level variable $Number\ FTE$, which is the year-to-year change in the number of employees in full-time equivalents. Tests on the following bank-level variables are reported: *Equity* is the the year-to-year change in the share of equity over total assets, $Cost-to-income$ is the year-to-year change in the cost to income ratio, *Return on assets* is the year-to-year change in the return on total assets, and *Liquidity* is the year-to-year change in the share of liquid assets over total assets. All bank-level variables are winsorized at the top and bottom 1% percentile. Furthermore, *Assets* is the year-to-year change in the log of total assets (in million EUR). Total assets is winsorized before being transformed into logs at the top and bottom 1% percentile. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | | Pre period | | | | Post period | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CHANGES** | N | Non-treated | Treated | Diff | SE | Non-treated | Treated | Diff | SE | DiD | SE |
| *Plant* | | | | | | | | | | | |
| Number FTE | 202,386 | 0.245 | 0.278 | 0.033 | 0.173 | 0.176 | 0.242 | 0.066 | 0.157 | 0.033 | 0.233 |
| *Bank* | | | | | | | | | | | |
| Equity | 5,351 | 0.012 | 0.101 | 0.089 | 0.056 | 0.551 | 0.575 | 0.023 | 0.040 | -0.065 | 0.068 |
| Cost-to-income | 5,350 | -1.776 | -1.797 | -0.021 | 0.576 | -0.348 | -0.392 | -0.044 | 0.410 | -0.023 | 0.707 |
| Return on assets | 5,351 | 0.011 | 0.015 | 0.004 | 0.012 | 0.001 | 0.002 | 0.001 | 0.009 | -0.003 | 0.015 |
| Liquidity | 5,351 | -1.018 | -0.992 | 0.026 | 0.403 | -0.757 | -0.645 | 0.111 | 0.286 | 0.085 | 0.494 |
| Assets | 5,351 | 0.036 | 0.029 | -0.007 | 0.006 | 0.025 | 0.022 | -0.003 | 0.004 | 0.004 | 0.008 |

Table 4: Probability of default of plants in difference-in-differences setting

This table reports the results from difference-in-differences analyses at the plant level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma SMP_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 28,144 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable *Exit* is an indicator that equals 1 if plant $i$ exits the market in year $t$ and 0 otherwise. *SMP* is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets. *Post* is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls ($X_{it-1}$) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant ($\alpha_i$), region-time ($\alpha_{rt}$), and sector-time ($\alpha_{kt}$) fixed effects are added. *Mean Exit* reports the mean of the dependent variable in the regression sample, and *SD Exit* is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | I | II | III | IV | V |
|---|---|---|---|---|---|
| Post*SMP | -0.003* | -0.004** | -0.005** | -0.005** | -0.005** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Firm age | Yes | Yes | Yes | Yes | Yes |
| Bank controls | - | Yes | Yes | Yes | Yes |
| Plant FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | - | - | - |
| Region-Time FE | - | - | Yes | - | Yes |
| Sector-Time FE | - | - | - | Yes | Yes |
| N | 202,386 | 202,386 | 202,386 | 202,386 | 202,386 |
| R2 | 0.248 | 0.248 | 0.250 | 0.251 | 0.253 |
| Mean Exit | 0.023 | 0.023 | 0.023 | 0.023 | 0.023 |
| SD Exit | 0.150 | 0.150 | 0.150 | 0.150 | 0.150 |

Table 5: Placebo treatment across plants and over time

This table reports the results from placebo difference-in-differences analyses at the plant level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma SMPplacebo_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 28,144 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable *Exit* is an indicator that equals 1 if plant $i$ exits the market in year $t$ and 0 otherwise. *Post* is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. In column I, the treatment *SMPplacebo* is assigned randomly across plants according to the overall treatment share. In column II, the treatment *SMPplacebo* is assigned randomly across plants per year according to the yearly treatment share. In column III, the treatment *SMPplacebo* is assigned randomly across plants and years according to the overall treatment share. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls ($X_{it-1}$) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant ($\alpha_i$), region-time ($\alpha_{rt}$), and sector-time ($\alpha_{kt}$) fixed effects are added. *Mean Exit* reports the mean of the dependent variable in the regression sample, and *SD Exit* is the standard deviation. Standard errors are clustered at the bank level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | I | II | III |
|---|---|---|---|
| Post*SMPplacebo | 0.001 | 0.002 | 0.001 |
| | 0.002 | 0.002 | 0.002 |
| Firm age | Yes | Yes | Yes |
| Bank controls | Yes | Yes | Yes |
| Plant FE | Yes | Yes | Yes |
| Region-Time FE | Yes | Yes | Yes |
| Sector-Time FE | Yes | Yes | Yes |
| N | 202,386 | 202,386 | 202,386 |
| R2 | 0.253 | 0.253 | 0.253 |
| Mean Exit | 0.023 | 0.023 | 0.023 |
| SD Exit | 0.150 | 0.150 | 0.150 |

Table 6: Marginal effects conditional on weak banks and firms

This table reports marginal effects of the treatment $SMP$ in the post period 2010-2013 derived from the following estimation: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 28,144 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. Table A.2 reports the underlying regression table. The dependent variable $Exit$ is an indicator that equals 1 if plant $i$ exits the market in year $t$ and 0 otherwise. $SMP$ is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $WB$ is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of the equity ratio in the year 2007. $WF$ is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls ($X_{it-1}$) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant ($\alpha_i$), region-time ($\alpha_{rt}$), and sector-time ($\alpha_{kt}$) fixed effects are added. Column I reports the marginal effects of $SMP$ for all firm-bank observations. Column II reports the marginal effects of $SMP$ conditional on the bank weakness indicator $WB$. Column III reports the marginal effects of $SMP$ conditional on bank and firm weakness. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | | I | II | III |
|---|---|---|---|---|
| All | | -0.005** | | |
| | | (0.002) | | |
| Banks | strong | | -0.002 | |
| | | | (0.003) | |
| | weak | | -0.008*** | |
| | | | (0.003) | |
| Strong banks | strong firms | | | -0.005 |
| | | | | (0.003) |
| | weak firms | | | 0.004 |
| | | | | (0.006) |
| Weak banks | strong firms | | | -0.008** |
| | | | | (0.003) |
| | weak firms | | | -0.010** |
| | | | | (0.004) |
| N | | 202,386 | 202,386 | 202,386 |
| R2 | | 0.253 | 0.253 | 0.253 |
| Mean Exit | | 0.023 | 0.023 | 0.023 |
| SD Exit | | 0.150 | 0.150 | 0.150 |

Table 7: T-tests on mean changes at the region and sector levels

This table shows t-tests on year-to-year changes in variables at the region and sector levels during the pre period between treated and control groups. Regions or sectors are defined as treated if the treatment share is above the median of all regions or sectors. The control group consists of regions or sectors that have a treatment share that is below the median. The sample covers the years 2007-2009. For first differences in the year 2007, observations from the year 2006 are also considered. The table reports tests on the following variables: *Entry* is the mean year-to-year change in entry rates at the region or sector level. *Exit* is the mean year-to-year change in exit rates at the region or sector level. *GDP per capita* is the mean year-to-year change in GDP per capita at the region level. *Number of plants* is the mean year-to-year change in the number of plants per region or sector. *FTE per plant* is the mean year-to-year change in the number of employees per plant in full-time equivalents. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | High treat | N | Low treat | N | Difference | t-stat |
|---|---|---|---|---|---|---|
| *Region* | | | | | | |
| Entry | -0.002 | 603 | -0.001 | 603 | 0.000 | 0.792 |
| Exit | -0.001 | 603 | 0.000 | 603 | 0.001 | 1.425 |
| GDP per capita | 351.672 | 597 | 303.561 | 603 | -48.111 | 0.495 |
| Number of plants | 55.566 | 603 | 44.050 | 603 | -11.516* | 2.461 |
| FTE per plant | -0.053 | 603 | -0.040 | 603 | 0.013 | 0.869 |
| *Sector* | | | | | | |
| Entry | -0.000 | 99 | 0.002 | 99 | 0.002 | 0.571 |
| Exit | 0.018 | 99 | 0.017 | 99 | -0.002 | -0.423 |
| Number of plants | 427.626 | 99 | 1321.131 | 99 | 893.505** | 3.221 |
| FTE per plant | -1.435 | 99 | -0.200 | 99 | 1.235** | 2.769 |

Table 8: More than 10 million plant-year observations aggregated

This table reports the results from difference-in-differences estimations at the aggregate level from the following regression: $Y_{rt/kt} = \alpha_{r/k} + \alpha_t + \gamma SMPshare_{r/k} \times Post_t + \epsilon_{rt/kt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated at the region $r$ or sector $k$ level. The dependent variables are mean entry and mean exit rates per region or sector. The data cover 402 regions and 66 sectors. *Post* is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per region or sector. $Mean$ *dependent* reports the mean of the dependent variable in the regression sample, and $SD$ *dependent* is the standard deviation. $Mean\ SMPshare$ reports the mean of the SMP share over all regions or sectors, and $SD\ SMPshare$ is the standard deviation. Standard errors are clustered at the region or sector level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | Region | | Sector | |
|---|---|---|---|---|
| | Entry | Exit | Entry | Exit |
| | I | II | III | IV |
| Post*SMPshare | -0.007*** | -0.004*** | -0.023 | -0.027** |
| | (0.001) | -0.001 | (0.022) | (0.012) |
| Time FE | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | - | - |
| Sector FE | - | - | Yes | Yes |
| N | 2,814 | 2,814 | 462 | 462 |
| R2 | 0.782 | 0.746 | 0.782 | 0.880 |
| Mean dependent | 0.050 | 0.055 | 0.055 | 0.055 |
| SD dependent | 0.010 | 0.009 | 0.030 | 0.028 |
| Mean SMPshare | 0.418 | 0.418 | 0.476 | 0.476 |
| SD SMPshare | 0.188 | 0.188 | 0.106 | 0.106 |

Table 9: Low-productivity regions drive lower entry and exit rates

This table reports the results from difference-in-differences estimations at the aggregate level from the following regression: $Y_{rt} = \alpha_t + \alpha_r + \gamma SMPshare_r \times Post_t \times Indicator_r + \cdots + \epsilon_{rt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated at the region level. The dependent variables are mean entry rates (columns I-III) and mean exit rates (columns IV-VI). The data cover 402 regions. *Post* is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. *SMPshare* is the share of treated plants per region. *Indicator* equals 1 in column I if the mean plant size in terms of the number of employees in full-time equivalents in region $r$ is above the mean of all regions, 0 otherwise. In column II, *Indicator* equals 1 if mean labor productivity, measured according to the turnover per employee, is below the mean of all regions. Turnover is extrapolated from firm information available from Amadeus from our matched bank-firm-plant sample. In column III, *Indicator* equals 1 if the average wage per full-time equivalent is below the mean of all regions. In columns IV-VI, *Indicator* is defined accordingly. *Mean dependent* reports the mean of the dependent variable in the regression sample, and *SD dependent* is the standard deviation. *Mean SMPshare* reports the mean of the SMP share over all regions, and *SD SMPshare* is the standard deviation. Standard errors are clustered at the region level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | | Entry | | | Exit | |
|---|---|---|---|---|---|---|
| | Size | Turn | Wage | Size | Turn | Wage |
| | I | II | III | IV | V | VI |
| Post*SMPshare | -0.005*** | -0.004*** | -0.004*** | -0.002 | -0.002 | -0.004*** |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| Post*Indicator | 0.000 | 0.002* | 0.000 | 0.001 | 0.002*** | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Post*SMPshare*Indicator | -0.002 | -0.004** | -0.004* | -0.004* | -0.005** | 0.000 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,814 | 2,814 | 2,814 | 2,814 | 2,814 | 2,814 |
| R2 | 0.783 | 0.783 | 0.784 | 0.747 | 0.747 | 0.746 |
| Mean dependent | 0.050 | | | 0.055 | | |
| SD dependent | 0.010 | | | 0.009 | | |
| Mean SMPshare | 0.418 | | | 0.418 | | |
| SD SMPshare | 0.188 | | | 0.188 | | |

Table 10: Low exit rates are driven by sectors with large plants

This table reports results from difference-in-differences estimations at the aggregate level from the following regression: $Y_{kt} = \alpha_t + \alpha_k + \gamma SMPshare_k \times Post_t \times Indicator_k + \cdots + \epsilon_{kt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated at the sector level. The dependent variables are mean entry rates (columns I-III) and mean exit rates (columns IV-VI). The data cover 66 sectors. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per sector. $Indicator$ equals 1 in column I if the mean plant size in terms of the number of employees in full-time equivalents in sector $k$ is above the mean of all sectors, 0 otherwise. In column II, $Indicator$ equals 1 if mean labor productivity, measured according to the turnover per employee, is below the mean of all sectors. Turnover is extrapolated from firm information available from Amadeus from our matched bank-firm-plant sample. In column III, $Indicator$ equals 1 if the average wage per full-time equivalent is below the mean of all sectors. In columns IV-VI, $Indicator$ is defined accordingly. $Mean\ dependent$ reports the mean of the dependent variable in the regression sample, and $SD\ dependent$ is the standard deviation. $Mean\ SMPshare$ reports the mean of the SMP share over all sectors, and $SD\ SMPshare$ is the standard deviation. Standard errors are clustered at the sector level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | | Entry | | | Exit | |
|---|---|---|---|---|---|---|
| | Size | Turn | Wage | Size | Turn | Wage |
| | I | II | III | IV | V | VI |
| Post*SMPshare | -0.036 | -0.018 | -0.009 | 0.015 | -0.039** | -0.052*** |
| | (0.025) | (0.034) | (0.035) | (0.014) | (0.015) | (0.017) |
| Post*Indicator | -0.003 | 0.004 | 0.018 | 0.021** | -0.015 | -0.028** |
| | (0.018) | (0.016) | (0.020) | (0.009) | (0.010) | (0.011) |
| Post*SMPshare*Indicator | 0.012 | 0.005 | -0.043 | -0.053*** | 0.035* | 0.064*** |
| | (0.041) | (0.038) | (0.045) | (0.019) | (0.020) | (0.022) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 462 | 462 | 462 | 462 | 462 | 462 |
| R2 | 0.782 | 0.784 | 0.783 | 0.883 | 0.881 | 0.883 |
| Mean dependent | 0.055 | | | 0.055 | | |
| SD dependent | 0.030 | | | 0.028 | | |
| Mean SMPshare | 0.476 | | | 0.476 | | |
| SD SMPshare | 0.106 | | | 0.106 | | |

# 7 Figures

Figure 1: Varying weak bank indicator

This figure depicts marginal effects and confidence bands at the 5% level of the treatment $SMP$ in the post period 2010-2013 conditional on varying weak bank indicators derived from the following estimations: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB\_X_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 28,144 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant $i$ exits the market in year $t$ and 0 otherwise. $SMP$ is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $WF$ is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. $WB\_X$ is a bank weakness indicator that equals 1 if the bank was in the lower X% percentile in terms of the equity ratio in the year 2007. We run 99 regressions and vary $WB\_X$ over 99 percentiles. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls ($X_{it-1}$) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant ($\alpha_i$), region-time ($\alpha_{rt}$), and sector-time ($\alpha_{kt}$) fixed effects are added. Standard errors are clustered at the bank level.

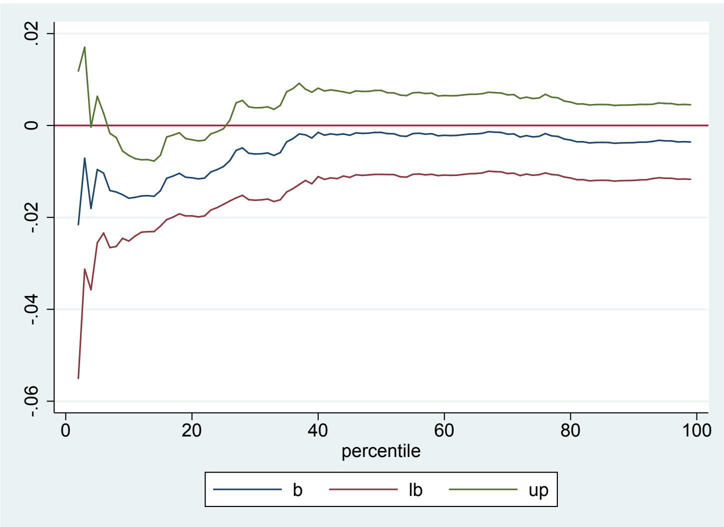


Figure 2: Varying weak firm indicator

This figure depicts marginal effects and confidence bands at the 5% level of the treatment $SMP$ in the post period 2010-2013 conditional on varying weak firm indicators derived from the following estimations: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF\_X_i + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 28,144 firms with 31,877 plants or 202,386 plant-year observations for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant $i$ exits the market in year $t$ and 0 otherwise. $SMP$ is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $WB$ is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of equity ratio in the year 2007. $WF\_X$ is a firm weakness indicator that equals 1 if the firm was in the lower X% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. We run 99 regressions and vary $WF\_X$ over 99 percentiles. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls ($X_{it-1}$) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant ($\alpha_i$), region-time ($\alpha_{rt}$), and sector-time ($\alpha_{kt}$) fixed effects are added. Standard errors are clustered at the bank level.

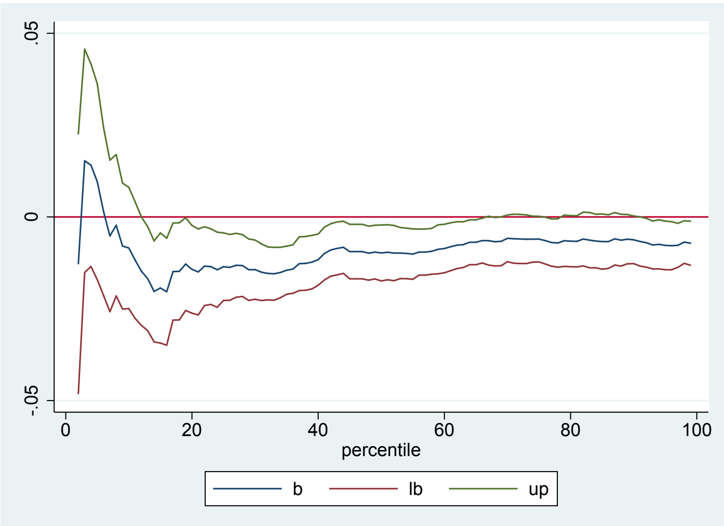
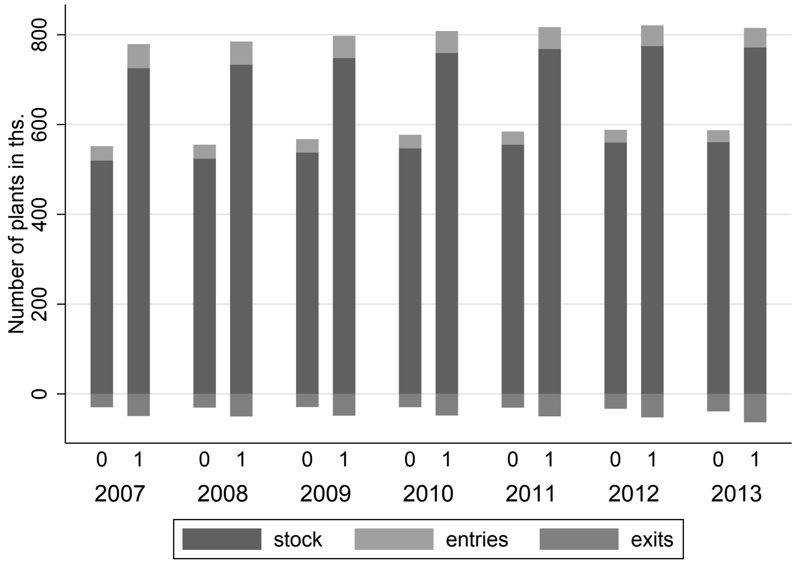


Figure 3: Number of plants per year conditional on treatment share of region

This figure depicts the number of plants per year in thousands. We categorize plants as belonging to the stock of plants, entering that year (entries), or exiting that year (exits). Furthermore, we distinguish between exposed and unexposed regions. Regions in which the share of treated plants based on our matched bank-firm-plant sample is below the median are considered to be unexposed (0), while regions that exhibit a treatment share above the median are considered to be exposed (1).



# A Appendix

Table A.1: Variable descriptions

| Variable | Unit | Description |
|---|---|---|
| *Plant variables. Source: IAB.* | | |
| Exit | 0/1 | Equals 1 in the year a plant exits the market, 0 otherwise. We use the definition of Hethey and Schmieder (2010) on small and atomized deaths. |
| Age | Years | Age of plant in years. |
| Number FTE | Employees | Number of employees in full-time equivalents. |
| *Bank variables, winsorized at lower and upper 1%. Source: Bankscope.* | | |
| Equity ratio | % | Equity over total assets. |
| Cost-to-income ratio | % | Overhead over net interest revenue plus other operating income. |
| Return on assets | % | Net income over total assets. |
| Liquidity ratio | % | Liquid assets over total assets. |
| Log of assets | Log mil EUR | Log million EUR total assets, winsorized before taking logs. |
| *Aggregate variables. Source: IAB.* | | |
| Entry rate | [0;1] | Mean entry rate per region (sector). |
| Exit rate | [0;1] | Mean exit rate per region (sector). |
| *Bank Weakness Indicator. Source: Bankscope.* | | |
| WB | 0/1 | Equals 1 if a bank's equity ratio was in the lower 25% percentile in 2007. |
| *Firm Weakness Indicator. Source: Amadeus and IAB.* | | |
| WF | 0/1 | Equals 1 if a firm's turnover/employee was in the lower 25% percentile in 2007 in its sector. As turnover is available only at the firm level, the WF indicator is the same within firms across plants. |

Variable descriptions continued

| Variable | Unit | Description |
|---|---|---|
| *Treatment variables. Source: Bundesbank and ECB.* | | |
| SMP | 0/1 | Equals 1 if bank held SMP-eligible assets in all three treatment years 2010, 2011 and 2012. |
| SMPshare | [0;1] | Share of treated plants in a region or sector. Extrapolated from merged sample of plant-level data with firm and bank information. |
| *Time indicator* | | |
| Post | 0/1 | Equals 0 in years 2007-2009 and 1 in years 2010-2013. |

## Table A.2: Regression results conditional on weak banks and firms

This table reports results from difference-in-differences analyses at the plant level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 28,144 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. Table 6 reports the marginal effects of $SMP$ conditional on time, firm and bank weakness. The dependent variable *Exit* is an indicator that equals 1 if plant $i$ exits the market in year $t$ and 0 otherwise. $SMP$ is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets. *Post* is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $WB$ is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of the equity ratio in the year 2007. $WF$ is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls ($X_{it-1}$) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant ($\alpha_i$), region-time ($\alpha_{rt}$), and sector-time ($\alpha_{kt}$) fixed effects are added. *Mean Exit* reports the mean of the dependent variable in the regression sample, and *SD Exit*is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | I | II | III |
|---|---|---|---|
| Post*SMP | -0.005** | -0.002 | -0.005 |
| | 0.002 | 0.003 | 0.003 |
| Post*WB | | -0.001 | 0.000 |
| | | 0.002 | 0.002 |
| Post*SMP*WB | | -0.006 | -0.003 |
| | | 0.004 | 0.004 |
| Post*WF | | | -0.003 |
| | | | 0.002 |
| Post*SMP*WF | | | 0.008 |
| | | | 0.007 |
| Post*WB*WF | | | -0.002 |
| | | | 0.003 |
| Post*SMP*WB*WF | | | -0.011 |
| | | | 0.008 |
| Firm age | Yes | Yes | Yes |
| Bank controls | Yes | Yes | Yes |
| Plant FE | Yes | Yes | Yes |
| Region*Time FE | Yes | Yes | Yes |
| Sector*Time FE | Yes | Yes | Yes |
| N | 202,386 | 202,386 | 202,386 |
| R2 | 0.253 | 0.253 | 0.253 |
| Mean Exit | 0.023 | 0.023 | 0.023 |
| SD Exit | 0.150 | 0.150 | 0.150 |

Table A.3: Leads and lags for region and sector estimations

This table reports the results from leads and lags estimations at the aggregate level from the following regression: $Y_{rt/kt} = \alpha_{r/k} + \alpha_t + \sum_{t=2007,\, t\neq 2009}^{2013} \gamma_t D_t \times SMPshare_{r/k} + \cdots + \epsilon_{rt/kt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated at the region $r$ or sector $k$ level. The dependent variables are the mean entry and mean exit rates of a region or sector. The data cover 406 regions and 66 sectors. $D_t$ are year indicators, excluding year 2009. $SMPshare$ is the share of treated plants per region or sector. *Mean dependent* reports the mean of the dependent variable in the regression sample, and *SD dependent* is the standard deviation. *Mean SMPshare* reports the mean of the SMP share over all regions or sectors, and *SD SMPshare* is the standard deviation. Standard errors are clustered at the region or sector level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

| | Region | | Sector | |
|---|---|---|---|---|
| | Entry | Exit | Entry | Exit |
| | I | II | III | IV |
| 2007*SMPshare | 0.004** | 0.001 | 0.004 | -0.008 |
| | (0.002) | (0.002) | (0.015) | (0.032) |
| 2008*SMPshare | 0.000 | 0.000 | 0.044 | 0.030 |
| | (0.002) | (0.002) | (0.041) | (0.022) |
| 2010*SMPshare | -0.004** | -0.002 | -0.026* | -0.011 |
| | (0.002) | (0.002) | (0.013) | (0.008) |
| 2011*SMPshare | -0.003* | -0.003** | -0.028** | -0.047*** |
| | (0.002) | (0.002) | (0.011) | (0.010) |
| 2012*SMPshare | -0.006*** | -0.007*** | -0.026 | 0.002 |
| | (0.002) | (0.002) | (0.016) | (0.019) |
| 2013*SMPshare | -0.008*** | -0.003 | 0.054 | -0.022 |
| | (0.002) | (0.002) | (0.040) | (0.016) |
| Region FE | Yes | Yes | - | - |
| Sector FE | - | - | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| N | 2,814 | 2,814 | 462 | 462 |
| R2 | 0.784 | 0.747 | 0.792 | 0.884 |
| Mean Dependent | 0.050 | 0.055 | 0.055 | 0.055 |
| SD Dependent | 0.010 | 0.009 | 0.030 | 0.028 |
| Mean SMPshare | 0.418 | 0.418 | 0.476 | 0.476 |
| SD SMPshare | 0.188 | 0.188 | 0.106 | 0.106 |

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