research paper series

Globalisation, Productivity and Technology

Research Paper 2019/12

R&D and firm resilience during bad times

Apoorva Gupta

R&D and firm resilience during bad times *

Apoorva Gupta †

January 2019

Find the latest version **here**

Abstract

Can being innovative help firms to shield themselves from the disruptive effects of a crisis? Using firm-level data for the Spanish manufacturing sector, this paper finds that innovative firms suffered considerably less compared to non-innovative firms during the Great Recession. This effect is explained by innovative firms differentiating their products to adapt to an unexpected rapid decline in economic activity. The data does not support alternative mechanisms such as reduction in marginal cost of production with process innovation, better access to capital, difference in labour moving costs, or higher technological diversification for innovative firms. The results provide evidence of the role of R&D in making firms dynamically capable and resilient to large negative shocks, adding another element to its well established role of facilitating growth through innovation and learning.

JEL Classification: L25, O30, O31, E32

Keywords: R&D, Crisis, Resilience, Product differentiation, Dynamic capability

*I am grateful to Richard Kneller and Omar Licandro for their invaluable guidance. I thank Joel Stiebale and Maria Garcia-Vega, and seminar participants at Aarhus University, Loughborough School of Business and Economics, University of Nottingham, 45^{th} EARIE (Athens), RES Annual conference (Sussex), 19th Conference on International Economics (Vila-Real), 17th GEP/CEPR Postgraduate conference (Nottingham) and 16th ETSG conference (Florence) for useful comments. I also thank Fundación SEPI for providing the data on Spanish manufacturing firms, and Ali Saadatnia for helping me with the data. All errors are mine.

†School of Economics, University of Nottingham, UK; Email: apoorva.gupta@nottingham.ac.uk

1 Introduction

The positive relationship between innovation, firm performance and aggregate economic growth has long been understood (Schumpeter, 1934; Romer, 1990). However, our understanding of these relationships is generally framed with a focus on long run growth absent of business cycle fluctuations. Whether, and how, being innovative matters for firms when an economy plunges into a crisis, an event that differs in intensity from periods of growth, and rapidly modifies existing markets, remains an open question.[1] This gap in the literature is the focus of this paper.

This paper analyses if being innovative makes firms resilient to large negative shocks. I focus on the Great Recession of 2008, and use data for Spain, a country that was severely affected by it. The Great Recession was an unanticipated shock for the global economy, and provides a natural experiment to study the relationship between firm innovativeness and growth in bad times. Using panel data for Spanish manufacturing firms, the key finding of this paper is that innovative firms, defined as firms with high R&D intensity prior to the crisis, were less adversely affected compared to non-innovative firms in sectors that were severely hit during the crisis. This effect is explained by innovative firms investing relatively more in product differentiation to adapt to rapid changes in business conditions during the crisis. The finding is supported by a strand of management literature which suggests that R&D investment makes a firm dynamically capable, that is being innovative allows a firm to reconfigure and renew itself to adapt to and capitalise on changes in the external environment (Teece and Pisano, 1994; Winter, 2003). In my knowledge, this paper is one of the first empirical works to provide direct evidence of the role of R&D in making firms resilient and dynamically capable.

The paper uses a conceptual framework that outlines the interplay between firm innovative potential, firm performance, and negative demand shocks to motivate the empirical strategy. Firm level data is sourced from a survey of Spanish manufacturing firms named

[1] The literature shows that during a crisis, consumer preferences change owing to a fall in income (Fajgelbaum et al., 2011), unproductive firms close down (Caballero and Hammour, 1994) leaving vacant markets for firms to participate in, assets become cheaper (Aghion and Saint-Paul, 1998) allowing firms to invest and grow etc.

Encuesta sobre Estrategias Empresariales (ESEE). Following the framework, the econometric strategy analyses the relationship between firm performance *during* the crisis, measured by real sales growth, and firms' innovativeness, measured by it's *pre-crisis* R&D intensity interacted with the intensity of shock that hit firms. For identification, I exploit variation in the severity of the Great Recession across industries using decline in the exports of Spain to the world by industry. Since exports are more likely to be driven by demand in the world markets than by internal supply shocks, the shock in all probability is exogenous to firm performance. The persistence of R&D over time and the fact that firm innovativeness is defined using R&D intensity prior to the crisis attenuates concerns of unobservable firm-level time variant characteristics driving the results. I also study firm performance in terms of real sales growth and that differences out any time invariant unobservable firm characteristics affecting the level of sales of a firm. I find convincing evidence that innovative firms in sectors most affected by the crisis suffered lesser than non-innovative firms, that is innovative firms were capable of cushioning the negative effects of a recession more than their counterparts.

To address endogeneity concerns with the baseline measure of shock, I instrument the sectoral decline in exports of Spain by the corresponding decline in exports from the US to the World except Spain. There is high correlation between the IV and baseline measure of shock across industries, and results with the IV are similar to the baseline specification. An important concern with the baseline measure of shock could be that it is picking up unobserved industry heterogeneity such that innovative firms always perform better in the industries that suffered during the crisis. I run a placebo test wherein I use data for non-recessionary years to look at the relationship between firm growth and R&D intensity interacted with crisis intensity measure. Although, R&D mattered for firm growth in non-recessionary years on average, it did not matter more in sectors that were most affected during the crisis. Futher, by pooling the data for recessionary and non-recessionary years, I show that the volatility of growth of innovative firms is not low on average, that is while they suffer lesser in bad times, their growth is not significantly lower in good times.

I subject the main findings to a barrage of robustness tests. The baseline analysis is conditional on survival of firms during the crisis, and can suffer from selection of successful innovators. To allay this concern, I study the likelihood of survival, and find that survival of R&D intensive firms is higher in sectors that were severely affected by the crisis. The results are robust to using skill intensity at firm level as a proxy for innovative potential of a firm, measuring firm performance by value added growth, and augmenting the baseline specification with interaction of firm-level R&D and additional crisis characteristics such as the intensity of financial shock. I explore if R&D is picking up unobservable firm characteristics by augmenting the baseline specification with interaction of demand shock and firm characteristics correlated with firm level R&D, like productivity, size, and innovation output in the past. The results are robust to including these interactions.

That innovative firms are able to react differently to a large negative shock opens a new question of how. To explore the mechanism behind resilience of innovative firms, I study if innovative firms are investing relatively more in R&D when hit by a large negative shock. The answer is yes. Investing in R&D can improve firm performance by allowing firms to differentiate its products, improve its processes, or both. This paper provides evidence that the resilience of R&D intensive firms to negative shocks operates through product differentiation.

To study the role of product differentiation, I divide my sample by the relative importance of product differentiation across industries following the approach of Rauch (1999). Innovative firms in industries with a higher scope for product differentiation are the only ones that are able to attenuate the negative effects of a crisis. Moreover, innovative firms in the differentiated goods industries invest relatively more in capital goods for the purpose of product improvement, and on advertising their product compared to their counterparts in industries hit by a negative shock. These effects are not found for firms belonging to homogenous goods industries. This shows that product differentiation is an important means of adapting during the crisis for innovative firms.

An alternative explanation for the superior performance of innovative firms in bad times could be that they are able to reduce marginal cost through process innovation and consequently lower selling price to attract a larger customer base. To study this channel, I calculate marginal cost and markups following De Loecker and Warzynski (2012), but do not find support for it. Innovative firms in sectors most affected during the crisis show an increase in marginal cost, do not significantly change output or input price, and sell output at a lower markup. Evidence on increase in marginal cost supports the result that innovative firms engage in product differentiation in bad times because inexperience in production process of a new product can lead to inefficiency: as noted by Clark and Griliches (1984) "product introductions generally involve a start-up and debugging phase of varying length in which new equipment or new tasks are specified and learned".

A concern with the measure of firm innovativeness is that it may be proxying for other non-innovative aspects of a firm, such as its financing constraints. Since I have no convincing exogenous instrument for firm R&D intensity, I carefully test for alternative explanations. First, an important aspect of the recession of 2008 in Spain was a sudden drying up of liquidity in financial markets which could have directly affected growth of firms most likely to be financially constrained. If R&D intensive firms are less financially constrained, they could have grown because of better access to capital during the crisis. Second, Spain has a two-tier labour market, and differences in labour flexibility of innovative and non-innovative firms could explain the baseline result. Third, innovative firms on average produce a higher number of products and are well diversified. Their technological diversity could selectively protect them from product specific shocks. I test for these mechanisms by augmenting the baseline specification with interaction of crisis shock and variables measuring firms' likelihood of getting financially constrained during the crisis, proxies for labour moving cost, and diversity of output markets. Being innovative remains an important predictor of firm resilience even in the presence of these additional interactions.

Thus, taken together, the evidence shows that being innovative allows firms to differentiate their products to adapt to changes in business conditions, and partially mitigate the negative effects a crisis shock. The essence of our argument is that R&D activities creates a knowledge base that firms can tap into to adapt to changed preferences and demand during a recession.

This paper contributes to various strands of literature. The two faces of R&D are widely understood in the growth literature: first as a source for innovation (Aghion et al., 2014; Romer, 1994), and second as a source of absorptive capacity, that is a firms' ability to absorb and assimilate external information (Cohen and Levinthal, 1989; Griffith et al., 2003). Futher, Geroski (1998) argues that firms that do R&D and produce many innovations are likely to be more flexible or adaptable. The knowledge based view of the firm views a firm as a knowledge creating entity and argues that knowledge and the capability to create and utilise such knowledge are the most important sources of a firm's sustainable competitive advantage (Nonaka et al., 2000). This paper provides robust evidence for this additional role of R&D in making firms resilient to crises and dynamically capable. (Wang and Ahmed, 2007).

Recent work by Bernard and Okubo (2016) shows that product level churning increases after the peak of a recession, and promotes firm level growth.[2] Argente et al. (2018a) present a case-study to show how the introduction of a new product, Tide Pods, helped Procter & Gamble to slow down the aggregate decline in revenue that characterised the Great Recession period. Importance of the product margin is also discussed in Hombert and Matray (2018) who show that R&D intensive firms are protected from import competition because they are able to differentiate their products. This paper adds to this literature by showing that product differentiation is an important channel for innovative firms to mitigate the disruptive effects of a negative *demand* shock.

The paper also adds to the growing literature on firm characteristics that foster resilience during crises. Chodorow-Reich (2014) show that firms that had pre-crisis relationships with less healthy lenders had a lower likelihood of obtaining a loan following the Lehman bankruptcy, and reduced employment by more compared to pre-crisis clients of healthier lenders. Giroud and Mueller (2017) find that highly leveraged firms experienced significantly larger employment losses in response to declines in local consumer demand. Aghion et al. (2017) show that resilience of decentralised firms is stronger in industries which experienced a greater increase in turbulence, measured by product churn, during the Great

[2] They explain this finding using the 'trapped factors' idea by Bloom et al. (2013) wherein negative demand shocks reduce output and leave some production workers unemployed who can now be engaged in innovative activities.

Recession. There is evidence that firm size (Fort et al., 2013), ownership and governance structures (Alviarez et al., 2017; Alfaro and Chen, 2012) also affect a firm's ability to perform in turbulent environments. This paper provides evidence that an important characteristic of firms that matters for resilience to large negative shocks is its ability to innovate.

The rest of the paper proceeds as follows. Section 2 outlines the motivating framework and describes the data and econometric specification used in this paper. Section 3 presents the results on resilience of innovative firms to demand shocks, followed by robustness checks in section 4. Section 5 shows that R&D firms adapt along the product dimension and discusses alternate channels that could make R&D firms more resilient to a demand shock. Section 7 concludes and offers ideas for future work.

2 Empirical identification

This section discusses a simple framework to study the relationship between firm output and innovation in the presence of unanticipated demand shocks. I use this framework to motivate the empirical strategy adopted in this paper.

2.1 Motivating framework

A large number of firms draw the cost of doing R&D, θ from a Pareto distribution. R&D, denoted by R, is a measure of firm innovation effort and $R = 1/\theta$, $R \geq 0$. A firm exerting higher innovation effort has a higher innovation intensity I, such that $E[I|R] = R$. Innovation increases demand for a firms' products, thus the output demanded Y from a firm at time $t = 0$ is given by

$$Y_0 = a + b_0 R$$

where a is firm-specific demand due to branding, quality etc., and b is the increase in demand due to innovation effort at time 0.

At time $t = 1$, firms face an unanticipated *negative* demand shock, S. S is larger the more negative the demand shock is. I focus on negative demand shocks in this paper and do not extend the same framework to booms because the dynamics of recession are qualitatively different from those of booms (Hamilton, 1989). For instance, negative shocks are sharp and sudden, while positive shocks are typically smoother transitions. This directly affects the output of all firms by reducing demand proportionally to the severity of the shock, captured by c_1. It also changes the direct effect of innovation on demand which I capture by b. In addition, I model a differential effect of the shock, S on output demanded of innovative firms by d_1. The output demanded at $t = 1$ is given by

$$Y_1 = a + b_1 R + c_1 S + d_1 RS$$

The difference in output between $t = 1$ and $t = 0$ is

$$Y_1 - Y_0 = \Delta Y = (b_1 - b_0)R + c_1 S + d_1 RS \tag{1}$$

The goal of this paper is to estimate d_1, that is the differential effect of a negative demand shock on the performance of innovative firms. In equation 1, d_1 will be positive if firms with a higher innovation effort are able to adapt, and hence perform relatively better when they are hit by a big (more negative) shock. Note that differencing eliminates the problem of correlation with time-invariable firm specific component of the error term affecting demand.

2.2 Data and summary statistics

To investigate if R&D intensive firms perform relatively better when an economy is hit by a negative demand shock, I focus on performance of Spanish firms during the Great Recession. The recession, which was triggered by the collapse of Lehman Brothers in September 2008, was unexpected, and led to a precipitous decline in global demand. I use data for Spanish firms because Spain was hit severely during the recession, and the recession lasted for several years which allows exploration of firm performance in an environment of depressed demand. I source firm level data from a business strategy survey of firms in Spain, ESEE, and measure demand shock at industry level using exports data from COMTRADE.

Firm level data: ESEE

The analysis in this paper relies on a longitudinal survey of Spanish manufacturing firms named *Encuesta sobre Estrategias Empresariales* (ESEE).[3] The survey, published by Fundación SEPI, has been conducted every year since 1990. The survey is designed to be representative of the Spanish manufacturing sector across industries and size-segments. Firms with 10 to 200 workers are randomly sampled by industry and size groups, and about 5% of the firms in this group are retained in the survey. All firms with more than 200 workers are requested to participate, and the average collaboration rate is 64%. On average 1800 firms respond to the survey each year, and of this approximately 30% firms have more than 200 employees until the early 2000s, beyond which there is a reduction in the percentage of large firms. New firms are incorporated to minimise the deterioration of the initial sample, and to maintain representativeness with respect to the reference population.[4]

The survey contains data on innovation input of a firm such as R&D expenditure and skilled personnel employed. Approximately 34-37% firms every year report positive R&D expenditures. It includes variables measuring innovation output such as whether the firm recorded a product or process innovation, and number of patents registered. This data is also suitable to study product differentiation since it records cost of purchase of capital goods for product improvement, and advertisement expenses of firms.

In addition, the availability of firm accounting data such as total sales, number of employees, value added, and profit margin in the survey allows us to study firm performance during the Great Recession. The survey also has data on change in input and output prices

[3]For further information on the survey see: http://www.fundacionsepi.es/investigacion/esee/spresentacion.asp

[4]The survey captures information about the manufacturing sector only, which represents 20-30% of the aggregate employment and value added in Spain. This dataset has been previously used in many papers focussing on firm investment and growth (for example Guadalupe et al. (2012), Doraszelski and Jaumandreu (2013), and Garicano and Steinwender (2016).)

at firm level, thus making it possible to measure physical total factor productivity following following Ackerberg et al. (2015), and markups following De Loecker and Warzynski (2012). Appendix B describes the calculation of firm level price indices, physical TFP and markups using this data. Firms in the sample belong to 20 manufacturing industries based on two-digit Classification of Economic Activities in the European Community (NACE) classification.

I remove observations with negative value-added, and/or zero employees, and those where firms undergo any significant change such as a merger, acquisition or a firm spin-off. I focus on firm performance during the crisis, and measure its determinants using pre-crisis firm characteristics. Table A7 in appendix B defines the main variables used in this paper, and Table 1 presents summary statistics for the sample used in the baseline regression analysis. The average firm in this sample employs 231 people showing that the survey is skewed towards larger firms. Mean age, measured as the number of years since the year of incorporation is 31 years. Approximately 35% firms each year report R&D expenses. Firm sales during the crisis declined on average by 28.45%.

Measuring demand shock

To measure the severity of the the Great Recession across Spanish manufacturing industries, I calculate the percentage decline in exports at industry level during the crisis as the baseline measure of intensity of demand shock following Aghion et al. (2017). In using export growth as a measure of crisis intensity, an identifying assumption I make is that exports are driven by demand in the world markets, and not by internal supply shocks, hence making the shock exogenous to firm performance. This assumption is supported by Behrens et al. (2013) who use microdata for Belgium, a small open economy like Spain, and do not find support for supply side explanations for the trade collapse during the Great Recession. However, the assumption is relaxed later by using an instrument for decline in Spanish exports.

Data on Spanish exports to the world is sourced from the UN COMTRADE database. This is an international database on all bilateral imports and exports. Export data is available at two-digit SITC code level, and I map it to two-digit NACE using a probability based concordance described in detail in appendix B. I deflate annual nominal export values by the year specific Consumer Price Index of Spain to obtain real exports. Figure A.2 shows the evolution of Spanish exports before and during the Great Recession. Exports were growing by about 5% in 2006 and 8% in 2007, but declined by 1% in 2008 and 12% in 2009. I calculate the percentage change in exports as the two-year difference between two-year rolling average of export value for each industry.

$$Xgr_t = (\frac{X_{t+1}+X_t}{X_{t-1}+X_{t-2}} - 1) * 100$$

To calculate intensity of crisis, I look at the deviation of export growth from trend growth prior to the crisis. Specifically, Shock is defined as follows:

$$Shock = -(Xgr_{2008} - \frac{\sum_{2003}^{2007} Xgr_t}{5})$$

Thus higher the deviation from trend, bigger is the Shock. Figure A.3 plots the crisis shock for 19 industries in the data[5]. For most indusries, except Leather and Beverages, export growth was below trend during the crisis. Intermediate goods like metals and machinery were among the most adversely affected sectors, and consumption goods like food, meat products etc., were the least affected sectors. Bricongne et al. (2012) study the trade collapse during the recession of 2008, and find similar patterns across industries using French customs data.

Instrumental variable

A potential concern with the baseline measure of crisis shock is that if there is a supply side shock that negatively affects the performance of non-innovative firms as compared to innovative firms, and hence leads to a decline in aggregate exports of that sector, then the relationship between firm performance and interaction of Shock and firm innovation effort will be endogenous. To allay this concern, I use an instrument for decline in industry-level exports of Spain. Another source of endogeneity could be that when firms innovate

[5]I do not include 'Miscellaneous manufacturing sector' in the analysis since it includes heterogenous goods and hence average decline in exports for this sector will be a noisy measure of the shock experienced by firms.

successfully, that is when realised returns to R&D are higher, this can increase exports in that industry. Thus export growth at industry level and sales growth of a firm could be affected by the same firm specific shock. However, this channel would lead to a downward bias, and, if anything, the estimate would be a lower bound on the resilience of innovative firms. Nevertheless, using an instrumental variable mitigates this concern too.

I instrument the change in exports of Spain by the change in exports for the United States of America during the crisis assuming that export shock across industries was similar for these two countries. Recessions typically have a greater impact on durable versus non-durable goods (King and Rebelo, 1999), and intermediate versus consumption goods (Bricongne et al., 2012), thus making the sectoral impact of recessions dependent on characteristics of an industry, and not a country.

The exclusion restriction is that shocks to firm level performance in Spain are uncorrelated with decline in US exports during the crisis. It is unlikely that US exports are affected by Spanish demand or supply side factors since Spain is a small economy and a small trading partner of the US. Nonetheless, I subtract exports to Spain from the US to ensure the IV is exogenous to Spanish firm level performance. Thus, we expect decline in US exports to be a valid instrument for decline in Spanish exports during the crisis.

The instrument is calculated by deflating US exports by CPI of the US, measuring shock as the deviation from trend export growth as defined above. Figure A.4 shows the correlation between the baseline measure of crisis intensity, and that of the IV. The instrument is highly correlated with baseline measure of shock, suggesting that the intensity with which industries were hit across the world during the crisis was similar. .

2.3 Econometric specification

Following the framework in section 2, I estimate how firm real sales growth depends on firm level R&D intensity, and its interaction with demand shock using a difference-in-difference approach as follows:

$$\Delta Y_{ijt} = Y_{t+s} - Y_{t-1} = \alpha R_{ijt-1} + \beta R_{ijt-1} * Shock_j + \gamma x_{ijt-1} + \phi_{jt} + \phi_l + \epsilon_{ijt} \tag{2}$$

where Y is log value of real sales of firm i in industry j measured from $t-1$ to $t+s$ where $s \in \{0,1\}$. I deflate firm sales by firm specific output price index.[6] I focus on growth at $t+1$ to give firms the time to adapt to an unanticipated demand shock that hits the firm between $t-1$ and $t+1$. R is the research and development expenses of firm i as a percentage of sales measured at $t-1$. I use firm R&D expenditure prior to the year of shock so that it is weakly exogenous to the shock.[7] *Shock* is a measure of the intensity of demand shock measured at two-digit NACE industry level as described above.[8]

x are a set of firm level controls recognised as important determinants of growth, especially during a crisis,[9] and are significantly different for firms that do R&D and those that do not (See Table A1). This includes log of firm size and firm age, its export intensity, and TFP calculated using a translog production function following Ackerberg et al. (2015).

ϕ_{jt} are industry-by-year dummies such that β is identified from comparing firms within the same industry-year. This is important because if R&D intensive *industries* are on average more resilient to demand shocks in any given year then the mitigating effect of R&D on disruptive effects of a recession would be explained by industry-year specific characteristics, and not firm-specific abilities. ϕ_l are location dummies for the main plant of the firm in any of the 19 regions of Spain. They absorb any region-specific policies that could differentially affect the growth of innovative and non-innovative firms during the crisis.[10]

Standard errors are clustered at industry level, the level of variation of the shock variable, and I adjust degrees of freedom since I have a small number of clusters as suggested by Abadie et al. (2017). The key hypothesis I examine in this paper is whether $\beta > 0$, which

[6] I follow Jaumandreu and Lin (2018) to calculate firm level price index. See appendix B for details.

[7] Since R&D expenditures are very persistent across time (Bloom, 2007), I check the robustness of the results to using R&D expenditure in $t-5$. Going back in time to measure R&D reduces the concern of it being endogenous to unobservable timevariant firm characteristics.

[8] The direct effect of *Shock* on firm performance gets absorbed by industry-year fixed effects in the regression specification.

[9] See (Fort et al., 2013; Almunia et al., 2017; Foster et al., 2016).

[10] This could include R&D tax credits, however in Spain there is not much variation across regions in R&D tax credit.

would indicate that R&D intensive firms facing the biggest shock during the crisis were associated with better performance.

To maximise the use of data, I pool data for two cross-sections such that I measure firm characteristics prior to the peak of the recession in 2009 (see Figure A.2 in appendix B). For independent variables measured in 2007, growth is measured from 2007 to 2009, and for independent variables measured in 2008, growth is measured from 2008 to 2010[11]. I restrict the analysis upto 2010 since in this paper I want to focus on the Great Recession, which started in late 2008 and was followed by a Sovereign Debt Crisis in some European countries, including Spain in 2011.

3 Results

3.1 Descriptive analysis of the main result

Figure 1 shows the differential effect of the Great Recession on growth of innovative and non-innovative firms graphically. I divide firms into those with above and below mean pre-crisis R&D intensity into 2 industry groups; those that experienced a high demand shock during the crisis (below mean detrended export growth), and those that experienced a relatively mild demand shock (above mean detrended export growth). I plot the average real sales growth during the crisis of these four groups of firms on the y-axis, and show 95% confidence intervals. The average decline in sales of R&D intensive firms in sectors hit by a 'high' shock is 17.3%, and that of low R&D intensive firms is 28.3%, while in 'low' shock sectors the decline is 9.4% and 13.7% respectively. Thus, as excepted there is a decline in sales for all four groups during the crisis, and it is sharper for firms operating in sectors that were hit harder. However, R&D intensive firms suffer significantly lesser than other firms in sectors that were hit severely during the crisis. Thus, ex-ante R&D intensive firms are able to shield themselves from adverse outcomes of a recession.

[11]Since the recession had started in the fourh quarter of 2008 I check the robustness of the analysis to excluding the cross section for independent variables measured in 2008, and depent variable measured from 2008 to 2010.

3.2 Baseline result

Table 2 reports the results of the analysis following equation 2. To begin with, I study the relationship between *ex-ante* R&D intensity, measure of crisis intensity, and sales growth of a firm during the recession. In column (1), I find that on average R&D intensive firms performed better during the recession. A one percent increase in R&D intensity is associated with a significant 2.32 percent increase in sales growth. As expected, the relationship between intensity of crisis shock and firm sales growth is negative. A one percent increase in crisis intensity is associated with a 0.7 percent decrease in firm sales growth.

In Column (2), I introduce an interaction between firms' R&D intensity and the measure of crisis intensity, Shock. The coefficient on the interaction term is 0.148 with a standard error of 0.063. It is positive and significant which shows that R&D intensive firms in industries that experienced a greater shock (more negative detrended exports growth) were resilient and grew relatively more than other firms in that industry. The magnitude is not trivial and shows that a shock of 1% will lower the sales of an average firm with no R&D by 0.81%, but will lower sales by 0.67% for a firm with 1% R&D intensity. The resilience of innovative firms increases as the intensity of R&D increases. The coefficient on R&D intensity is insignificant when the specification includes an interaction term, which shows that R&D intensive firms did not grow differentially in the sectors that had zero export growth. The coefficient on intensity of crisis is negative and significant.

In column (3) I control for firm observables such as size, age, export-sales ratio, and TFP, and include industry-year and location fixed effects. The coefficient on the interaction term is positive and significant supporting the hypothesis that R&D firms were more resilient to the crisis, and more so in sectors that were severely hit during the Great Recession.[12]

[12] I check the robustness of the result to minor changes in the baseline specification. Results are shown in in Table A2. In column (1), I use one-year difference in real sales growth instead of two-year differences as the dependent variable. In column (2) I report results without winsorising the dependent variable. Following Hombert and Matray (2018), in column (3), I measure firm innovative effort by calculating R&D stock by adding up previous R&D expenses of a firm and depreciating it annually at 15%, as a percentage of sales in $t-1$. In column (4), I use the five year lagged value of R&D intensity. In column (5), the crisis intensity measure is growth in exports without detrending it. Column (6) controls for several firm observables to allay concerns regarding firm unobservables. I control for total patents of a

Column (4) shows the results using an instrument variable for crisis intensity as defined above. The instrument is valid since the null for weak instruments is rejected with a p-value tending to zero. The F-statistic is 28.09 showing the validity of the first stage. The interaction term is positive and significant suggesting that R&D firms in industries that were affected more during the crisis were more resilient to the shock. The coefficient for the interaction term using IV estimation is similar to that obtained in column (3). The Durbin-Wu-Hausman test is not rejected, thus both, the coefficient with IV estimation and ordinary least square are consistent. However, since OLS is efficient, I present the rest of the analysis using detrended decline in export growth of Spain to measure the intensity of crisis across industries.[13]

Placebo test

A possible concern with the baseline measure of crisis intensity, and the instrument for it could be that it is picking up a time-invariant industry characteristic such that R&D firms in sectors that were hit severely perform better even in non-recessionary periods. For instance, if the crisis shock was more severe in industries with a high dispersion of R&D expenses, and R&D intensive firms always perform better in sectors with a high dispersion of R&D, then a positive β would be spurious.To address this concern, I study the relationship between firm growth and interaction of R&D intensity and shock as measured above, but for *pre-recession years.* If $Shock * R\&D$ is positive and significant in years prior to the crisis, then this would suggest that R&D firms always perform better in sectors that were hit during the crisis.

I use the same specification as in equation 2 but with sales growth measured over non-recessionary years, 2003-2005 and 2004-2006, and independent variables measured at the initial period, i.e. 2003 and 2004. Spain experienced strong economic growth in this period as seen in Figure A.2, and studying this period can let us see the difference in growth of

firm, whether or not it had a product, process, management or organisational innovation at $t-1$, its import intensity, asset tangibility, whether it is part of a group, its short-term debt as a ratio of its sales, and its self reported market share and whether it thinks the markets it is participating in are expanding, stable or in decline. The interaction of R&D-sales and export shock remains significant in all these modifications of the baseline specification.

[13] Results with using IV for Shock are available upon request.

innovative firms during recessions and booms. Results are shown in Table 3. Column (1) shows the relationship between R&D intensity and firm level growth, and column (2) shows how this relationship varies by the severity of crisis across sectors. Although *ex-ante* R&D intensive firms grow at a significantly higher rate in non-recessionary periods on average (the coefficient on R&D intensity is positive and significant in Columns 1 and 2), they do not perform better in sectors that experienced a larger demand shock during the recession (coefficient on interaction term is insignificant).[14] This suggests that our measure of crisis intensity is not picking up unobserved industry heterogeneity.

Are R&D firms particularly resilient to *bad* shocks, or is it that the output growth of R&D intensive firms is less volatile, and hence the interaction term is negative? Is it that innovative firms perform worse in *good* times? To study this, I pool data for pre-recession and recession years that is $t \in \{2004 - 2009\}$. In column (3), I interact R&D intensity with a dummy for the Great Recession, labelled GFC ($t \in \{2008, 2009\}$). The result shows that R&D intensive firms are associated with higher growth on average, and this effect is significantly stronger when $GFC = 1$. In column (4), I interact R&D*GFC with export growth for each industy year. It is calculated as Xgr_t defined above, for $t \in \{2004 - 2009\}$. For ease of interpretation, I multiply the growth by minus one so that a large decline is measured as a bigger shock. The coefficient on R&D intensity interacted with year-wise shock is not significant for the full sample, however both, R&D*GFC and triple interaction of R&D*GFC*Year-wise shock are positive and significant. This shows that R&D was a significant determinant of firm growth specifically during the crisis period, and mattered more for firms that were hit by a bigger shock (more negative). Thus *ex-ante* R&D intensive firms are resilient specifically to *bad* shocks. Their output growth is not less volatile, that is they do not perform relatively worse in non-recessionary periods or good times. Thus the relationship between R&D and firm performance is not symmetric in booms and recessions.[15]

[14] In this regression I also see that firms that grew during pre-recession years in Spain were significantly larger, in line with the findings of Gopinath et al. (2017) and García-Santana et al. (2016).

[15] A word of caution: Using export growth to measure sectoral performance is likely to be endogenous in pre-crisis years. Unlike during the crisis when decline in export growth was unanticipated and exogenous, during pre-recession years it is likely to be more predictable, and hence endogenous

Survival

A limitation of studying firm growth in the baseline specification is that it is conditional on survival of firms during the crisis. This could lead to a selection bias if firms that successfully innovated survived the recession, and those with unsuccessful R&D effort perished. This is possible since the outcome of R&D expenditures is subject to a high degree of uncertainty (Doraszelski and Jaumandreu, 2013), and the uncertainty is likely to be higher in bad times. Thus, if the probability of successfully innovating and hence surviving given R&D expenditure is 0.5, then the result of resilience of R&D intensive firms during crisis is due to sample selection. However, if R&D intensity in sectors that are hardest hit in the recession matters significantly for firm survival too, then the concern of sample selection of successful innovators is attentuated.

The firm level survey used in this paper is unsuitable for recognising firm exit since when a firm stops reporting it does not distinguish between a firm for which data are missing and a firm that closes down. Hence, for this analysis, I use the second-best option available in this data: an identifier that equals 1 if a firm closes down, changes to non-manufacturing activity, or is taken over. Survival is then a dummy variable equal to one for firms that are observable from $t-1$ to $t+1$, and 0 for firms that are observable in $t-1$ but not in t or $t+1$. Firms which stop reporting but do not give any reason for not reporting are dropped. I use a probit model to study firm survival as the dependent variable with the same specification as in equation 2. Column (1) in Table 4 show that the interaction of R&D and crisis intensity is positive and significant showing that R&D intensive firms were also more likely to survive in sectors that were severely hit in the crisis. In column (2), I use the instrument for crisis intensity as defined above, and the result is qualitatively similar. In column (3), I repeat the placebo test by looking at survival in non-recessionary years, and I find that the coefficient is not significant. Thus, along with suffering relatively lesser, innovative firms were also more likely to survive in sectors most severely affected during the crisis.

4 Robustness tests

In this section, I test the robustness of the resilience of R&D intensive firms when hit by a negative shock to modifications in measurement of firm performance, severity of the Great Recession, and firm innovative effort.

Alternative measures of firm performance

The analysis so far shows that R&D mitigates the disruptive effects of a crisis on firm sales growth. Table 5 shows the results for alternative measures of overall firm performance: (a) change in log of value-added from $t-1$ to $t+1$ in column (1), and (b) profit margin measured as the cumulative profit of a firm in t and $t+1$ normalised by sales in $t-1$ in column (2). The interaction term is positive and significant for value added growth but not for profit margin. Thus even though R&D firms are selling relatively more, it is not translating into higher profits. This is interesting because it suggests that R&D firms in particular were not affected by the shock, because if that were true, there should have been a positive and significant effect for all metrics of firm performance.

In columns (3) and (4), I explore if R&D intensive firms hire or invest relatively more to maintain their sales in a recession, or whether they downsize. In column (3), I estimate equation (2) with difference in log value of total employment from $t-1$ to $t+1$ as the dependent variable, and find that the key interaction term is positive but not significant. The lack of responsiveness in terms of employment could be because of labour adjustment costs which can make employment more sticky than firm output. The total number of employees also masks any changes in worker quality or the effort put in by each existing worker, which as shown by Lazear et al. (2016) increases in recessions.

In column (4), I estimate the effect on capital expenditures by calculating the cumulative investment in capital goods over two years (in t, and $t+1$) normalised by sales in $t-1$. The interaction term is positive and significant which suggests that R&D firms cut their capital expenditures relatively less than their counterparts when hit by a bad shock. More detailed information on the allocation of factors of production across products and markets could shed light on the channel through which R&D firms shield themselves. In section

5, I use available information on investment for the purpose of product improvement to suggest that R&D firms differentiate their products when hit severly by a negative shock.

Alternative measure of firm R&D intensity

To mitigate concerns regarding the use of R&D as a percentage of sales to measure firms' innovative potential in the baseline analysis, I replace it with skill intensity defined as percentage of engineers and graduates in the total workforce. Since a substantial portion of R&D labs is formed of skilled employees, I expect similar results with using skill intensity as a measure for innovative potential. The correlation between R&D intensity and skill intensity in my data is 1.05. This variable is reported every 4 years in the survey, so I use the value for 2006, the latest pre-crisis year in which it is available.

Results are reported in Table 7. Column (1) shows the result for the baseline specification where R&D intensity is replaced with skill intensity. In column (2) I use the instrument for crisis intensity, and in column (3) I repeat the placebo test discussed above by looking at growth in pre-recession years and using value of skill intensity in 2002. I find that the interaction term between Shock and skill intensity is positive and significant in columns (1) and (2), reaffirming the result that firms with high innovation potential are resilient to bad shocks. This is not so for non-recessionary years in column (3), allaying concerns of industry specific characteristics driving the result. Thus the resilience of innovative firms is robust to using different metrics for innovative ability of a firm.

Alternative measures of shock

The baseline proxy of shock experienced by firms during the crisis measures the shock experienced by firms due to a trade collapse, which as discussed above is exogenous to local supply shocks. I check the robustness of the resilience of R&D intensive firms to bad shocks by using measures of shock picking up regional variation in the intensity of the crisis (column 1 and 2), to the likelihood of getting financially constrained as liquidity froze (column 3 and 4), and to overall decline in industrial performance using gross value added by industry (column 5 and 6) in Table 6.

First, I calculate the percentage change in total number of firms by region in Spain wherein a higher decline in number of firms implies a larger shock, as firm exit increases and firm entry decreases in regions strongly affected by the crisis.[16] The coefficient on the interaction term between R&D and shock measured by percentage change in number of firms is positive but insignificant (column 1). This suggests that R&D firms did not perform relatively better in regions that were hit more severely. This could be because R&D firms in an industry are clustered in certain regions, or because there are large regional spillovers. In column (2), I additionally control for the main interaction term. I find that it is of similar magnitude to the baseline specification and is significant.

Second, I measure shock by studying the external financial dependence of a sector using the approach as in Rajan and Zingales (1998) which uses the difference between investments and cash generated from operations to calculate industry's need for external finance. Since the crisis of 2008 led to high liquidity constraint in Spain, I expect that industries more dependent on external finance would have experienced a bigger shock, and the lack of finance could have hampered firms' ability to grow (Nanda and Nicholas, 2014).[17] In column (3), the coefficient for interaction between R&D and financial dependence is positive but is not significant, suggesting that R&D firms did not perform better if they belonged to sectors that were more dependent on external finance. In column (4), I additionally control for our baseline interaction term, and the coefficient for it remains positive and significant. This suggests that innovative firms are particurly resilient to a demand shock, even after accounting for the liquidity shock experienced by firms.

Third, I calculate the detrended growth of Gross Value-Added at current prices for each industry and use this as a measure of the domestic shock experienced by a firm.[18] In column (5), the interaction term of industry output decline and R&D is negative and not statistically significant, however when I add the baseline interaction term in column (6),

[16] I source data from the Spanish Statistical Institute (INE) on the number of active companies by Autonomous Community (`http://www.ine.es/dynt3/inebase/en/index.htm?padre=54&capsel=3922`)

[17] I borrow the measure for financial dependence from Sharma and Winkler (2017), and use the mean value for NACE-2 digit level

[18] I source the data on Gross Value Added from INE, Spain and calculate the detrended growth rate in the same way as I calculate detrended export growth rate above. Due to lack of detailed data, I am able to calculate GDP shock measures for only 16 industry groups, as opposed to 19 industry groups in the baseline measure of shock.

the key interaction term is positive and significant. The lack of similar results with using industry output to measure industry level shock is not very surprising since the correlation between domestic output decline and exports across sectors is not highly correlated for Spain during the crisis. This is in line with Almunia et al. (2017) who find that firms whose domestic sales reduced by more during the crisis observed a larger increase in export flows, thus showing a potentially inverse relationship between domestic demand shock and external demand shock. Thus, the above analysis suggests that the resilience of R&D intensive firms is to the trade-induced demand shock, but not regional, financial or domestic shock.[19]

Horse race between firm characteristics correlated with R&D

A concern with the baseline estimation could be that R&D is a proxy for some unobservable firm characteristic and not firm innovative potential. I explore this by investigating if the main interaction term remains an important predictor of firm performance in bad times even when I control for firm level characteristics correlated with R&D. In Table 8, I augment the baseline specification with interaction between crisis intensity measure and total factor productivity (column 1), size, measured as log of number of employees (column 2), sales growth of a firm (column 3), and whether a firm had a product innovation (column 4), or process innovation (column 5) in $t-1$, that is before the shock is realised. The coefficient on the interaction term between R&D and shock remains significant even in the presence of extra interactions, and the value of the coefficient also remains similar. Thus, in the horse race of what matters for firm growth during recession, R&D intensity of a firm seems to be important, and not firm characteristics that are correlated with R&D and are a measure of pre-crisis success at firm level.

Another possible concern can be that the result is getting driven by quality of firm management. The literature does not provide any evidence of a strong correlation between management and R&D intensity of a firm, but if in our sample R&D intensive firms have

[19] It is also important to note that measures like decline in number of firms and GDP could be picking up both demand and supply shocks at firm level and could hence be endogenous to firm performance. For instance, in sectors that were hit by the crisis, if R&D firms innovated and grew, then GDP would increase and hence would not adequately measure shock during the crisis.

high quality management, and well-managed firms perform better when hit with a bad shock, then there would be an endogeneity problem. The data does not have a direct measure for management quality at firm level. However, (Bloom et al., 2013) suggests that well managed firms are more productive, and since I do not find any significant effect of the interaction of shock with productivity (column 1), it is unlikely that management quality is driving our result. Third, following the framework of my empirical strategy, I cannot include firm management as a fixed effect since firm fixed effect gets differenced out when we take first difference to study growth rates.

Summarising the robustness checks:

The basic character of results is consistently obtained across the range of robustness checks shown above.

5 Mechanism

This section explores the mechanism that allows R&D intensive firms to cushion the disruptive effects of a negative external demand shock. Do innovative firms innovate to adapt when they are hit by a negative shock? To study this, I first study the effect on innovation input as measured by R&D spending of a firm.

Table 9 estimates equation 2 with R&D expenses in t normalised by pre-crisis sales as the dependent variable in column 1, and R&D expenses cumulated over t and $t+1$ normalised by pre-crisis sales in column 2. The table shows that R&D expenses are higher for R&D intensive firms on average, but they are significantly higher for R&D intensive firms in sectors that were hit more severely during the crisis. This is in line with the theory of opportunity cost of productivity enhancing investment (Aghion and Saint-Paul, 1998). The opportunity cost of doing R&D falls in recessions as return from production declines, and hence firms invest more in R&D. A positive coefficient on the interaction between R&D intensity and severity of shock shows that it is the *ex-ante* R&D intensive firms that invest more in R&D when the opportunity cost of innovation declines. This could be because having an innovation base ex-ante allows R&D intensive firms to swiftly move from production to innovation when times are bad (Archibugi et al., 2013).

Investing in R&D can improve firm performance by allowing it to differentiate its products, improve its processes, or both. In times of a crisis, product differentiation can help a firm enter markets that continue to do well, access markets left vacant by exiting firms, and adapt according to changed consumer preferences. Process innovation on the other hand could enable them to reduce their cost of production of existing products and hence sell them at a lower price. I now explore if R&D firms differentiate their products, or reduce prices and marginal cost when hit by a negative shock.

5.1 Product differentiation

To study if product differentiation is important for resilience of innovative firms in a recession, I divide my sample by the relevance of product differentiation across industries using a classification scheme proposed by Rauch (1999). I use RAUCH classification at SITC two-digit level, map it to NACE two-digit and divide industries into those with relatively more differentiated goods, and those with more homogenous goods. I calculate this measure by assigning a dummy equal to 1 for goods that are differentiated, and 0 for others using the liberal classification. For each two-digit SITC industry group, I call it a differentiated sector if more than 50% of the products in that industry group are differentiated. I map SITC two-digit to NACE two-digit as described in appendix B. For each two-digit NACE group, if the difference between the frequency with which differentiated and homogenous products map into that group is greater than the median difference across industries, then I call it a differentiated sector. Table A3 shows the industry classification.

Results for the two sub-samples are reported in Table 10. R&D intensive firms in differentiated products industry groups perform relatively better when they are hit by a large negative shock (column 1), however this is not the case for industries with homogenous products (column 2). This shows that product differentiation is an important channel for resilience of innovative firms.

I test the robustness of the above result to using different measures of importance of product differentiation by industry: a) using EU KLEMS data to divide industries into above and below median R&D intensive as a measure of importance of quality differentiation (Kugler and Verhoogen, 2011) in columns (3) and (4) respectively, b) using OECD definition of whether a sector is technology intensive or not in columns (5) and (6), respectively (Organisation for Economic Co-operation and Development, 2011). The main interaction term is positive and significant in R&D intensive sectors (column 3) and technologically intensive sectors (column 5). This suggests that the scope to differentiate products is important for R&D firms to mitigate disruptive effects of a demand shock.

Do innovative firms differentiate more in recession?

To study if R&D intensive firms engage in product differentiation following a demand shock, I use data on a) the value of investment in capital goods specifically for product improvement, and b) firms' advertisement expenses, which I use as proxies for firms' product differentiation effort. An increase in investment for product improvement or advertisement expenses by R&D intensive firms hit by a large negative shock would suggest that these firms are changing their products to adapt to changed market conditions and consumer preferences during the crisis.[20]

I estimate equation 2 with a) cumulative expenditure on product improvement in t and $t+1$ normalised by pre-crisis sales, and b) cumulative advertisement expenses in t and $t+1$ normalised by pre-crisis sales as dependent variables. I study the effect on product differentiation for firms in industries with differentiated goods, and homogenous goods separately. Results are reported in Table 11. R&D intensive firms that were hit more severely during the crisis invested more in capital goods for product improvement in the sub-sample of industries with differentiated goods (column 1). The main interaction term for sample of industries with homogenous goods is positive but not significant (column 2).

[20]Papers studying product differentiation use data on products added and dropped by firms Bernard and Okubo (2016); Argente et al. (2018b). However this survey provides information only for the aggregate number of products produced by a firm in a year. This masks product churn at firm level. Variables like product innovation and number of product innovations also mask the degree of product differentiation, and are not comparable across firms in this survey. Table A4 shows results for binary indicator of whether a firm recorded a product innovation (column 1), and the number of product innovations (column 2) as the dependent variable. The coefficient for our key interaction term is not significant.

For advertisement expenses too, the interaction term is positive and significant for firms in industries with differentiated goods only (column 3), but not in industries with homogenous products (column 4). This shows that R&D firms in sectors with a high scope for product differentiation react to a negative shock by differentiating their products. Argente et al. (2018b) find that R&D intensive firms experience revenue growth by reallocating products, and this paper supports their work by showing that this is true even in recessions.[21]

5.2 Effect on cost and prices

Another possible mechanism for why R&D firms suffer lesser in a recession could be that they are able to reduce their cost of production and pass on the reduction in cost to prices by doing process innovation. In Table 12, I estimate equation 2 for the cumulative percentage change in input prices (column 1), and cumulative percentage change in output price at a two year horizon (column 2).[22] I find that the interaction term is not significant for both input and output price suggesting that R&D firms did not change their prices differentially to mitigate the effect of the downturn.

Using the same data, Jaumandreu and Lin (2018) show that process innovations decrease marginal costs, however product innovations either increase or do not affect marginal costs. An increase in marginal cost is conceivable for a new product because the firm has lesser experience in manufacturing this product, hence is less efficient, or is possibly producing a product different from its core competency (Eckel and Neary, 2010). I estimate equation 2 with the percentage change in marginal cost (column 3) and markup (column 4) at a two year horizon as the dependent variables to study if R&D firms focus on process or product innovation. I calculate marginal cost and markup following De Loecker and Warzynski (2012) which is explained in detail in appendix B. I find that marginal cost

[21]I use a firm reported measure on whether their products are customised or standardised to divide my sample, and study whether R&D intensive firms with customised products react to a negative shock by investing more in capital goods for product improvement and in advertisement. I find that firms with customised products invest in differentiating their products, but this is not the case with firm with standardised products. Results are available in the appendix.

[22]The survey directly reports percentage change in prices of intermediate consumption, which I call input prices, and the percentage change in price of output. I cumulate the change over two years, and winsorise it at 1% on both tails. The results are robust to changes in prices over a one year horizon

of R&D intensive firms that were hit severely by the recession is higher than other firms suggesting that innovative firms are not engaging in process innovation. This finding supports the result that R&D firms are engaging in product innovation during the crisis since new products imply adjustment costs that lower productivity in the short run.[23] Although marginal cost seems to be increasing, I do not see an increase in output prices, thus suggesting that these firms take a hit on their markup. In column (4), I see that the interaction term is negative and significant, showing that the markup of innovative firms that were hit with a severe shock are lower in the recession. The decline in markups could also explain why I don't see an effect on profit of firms in Table 5.

6 Alternative explanations

In arguing that being innovative makes firms capable of cushioning the negative effects of a crisis, I have shown that innovative firms grew relatively more during the Great Recession in Spain, and this effect operated through product differentiation. While it can be argued that the ability to spend on R&D and product differentiation are linked to the innovative potential of a firm, even during a crisis as seen above, in this section, I consider alternative theories that could explain the above results.

Financing constraints

During the Great Recession, liquidity froze and financially constrained suffered due to their inability to fulfill their working capital needs and invest in seemingly fruitful ventures. Existing evidence on whether financing constraints matter for R&D is decidedly mixed (Hall and Lerner, 2010), however if in my sample R&D firms were systematically financially less constrained, then their ability to grow and spend relatively more on differentiating their products could have been driven by their ability to raise enough capital during the crisis. I study this by augmenting the baseline regression described in equation 2 with

[23] Results for binary indicator of whether a firm recorded a process innovation (column 3) is reported in Table A4. The coefficient for our key interaction term is positive but not significant. I do not use this to discuss whether firms are engaging in process innovation because it masks the success of process innovation across firms which is captured by the change in marginal cost.

an interaction of the shock variable and a measure of firm financing constraint in $t-1$, and check if it makes R&D*Shock weaker and insignificant. I do this exercise with five measures of financing constraints identified in the literature.

Table 13 shows the results. Column (1) uses information on whether a firm is part of a business group, where business group firms are expected to be less financially constrained. Column (2) uses the short-term debt to sales ratio of a firm wherein firms with a high ratio of debt with less than one year maturity are likely to face higher financing constraints during the crisis (Garicano and Steinwender, 2016). Column (3) uses the percentage of foreign ownership of firms where foreign owned firms are expected to be less constrained. Column (4) uses firms debt to equity ratio as a measure of firm leverage, where firms with higher leverage are likely to be financially constrained. Column (5) uses the ratio of tangible assets to total assets of a firm to measure its ability to raise capital against collateral. Even after controlling for firm-level financing constraints interacted with Shock, the interaction of R&D intensity and demand shock is positive and significant and the coefficient magnitude is similar to the baseline. In line with Alfaro and Chen (2012), foreign owned firms perform relatively better in sectors most hit during the crisis, however being innovative continues to matter for firm resilience.

Labour moving costs

Temporary contracts is a widespread phenomenon in Spain, creating a two-tier labour market such that the cost of terminating temporary contracts is significantly lower than that of permanent jobs (Bentolila et al., 2012). When hit with a bad shock, firms with a higher share of permanent employees could thus prefer to hoard its employees, than incur the cost of moving them. Thus, as suggested by Bloom et al. (2013), factors of production could be temporarily 'trapped' within firms suffering from negative shocks due to high moving costs, and this excess capacity could force firms to rethink their strategies and use the factors of production more efficiently. If R&D firms have higher permanent employment, then the result could be driven by the presence of 'trapped factors' in a recession. I study this in Table 14 by augmenting the baseline regression with interactions of Shock and three variables that predict costs of moving labour.

Column (1) includes an interaction of the shock variable with the percentage of temporary staff, column (2) includes an interaction with percentage of part-time staff expecting that the smaller the percentage of temporary and part-time workers, the more likely it would be for the firm to have trapped factors. Column (3) includes an interaction with the expenditure on employee training as a percentage of sales wherein firms are expected to try to retain their employees if they have invested heavily in training them. I find that in all the models, the main interaction coefficient remains positive and significant, and the additional interaction term is not significant. This suggests that the presence of trapped factors in a firm alone cannot help it to mitigate the negative effects of a crisis. The firm needs to have the knowledge base or innovative potential to be able to differentiate its products in order to adapt to changed market space.

Technological diversification benefits

Koren and Tenreyro (2013) suggest that increases in technological diversity provide diversification benefits against variety specific shocks which in turn lower the volatility of output growth. Garcia-Vega (2006) show that R&D intensity increases with the degree of technological diversification of a firm. Thus if R&D intensive firms are selectively protected from bad shocks because they are more diversified, then the main result is spurious. To allay this concern, I augment the baseline specification with interactions of Shock and variables that proxy the diversity of input and output markets of a firm.

In Table 15, I add an interaction of Shock and number of products as an indicator of output and input markets (column 1), number of international markets of the firm (column 2), export intensity as a measure of international market diversification (column 3), and a dummy for product customisation because a firm producing customised products is likely to be more diversified (column 4), all measured in $t-1$. The coefficients on the additional interaction terms are not significantly different from zero (columns 1-4), suggesting that there were no important diversification benefits for innovative firms. Importantly, the coefficient on interaction of R&D and demand shock remains positive and significant with additional control for technological diversification.[24]

[24] Almunia et al. (2017) show that export markets were a means for Spanish firms to cushion the negative

In table A6 I estimate equation 2 with a) cumulative expenditure on product improvement in t and $t+1$ normalised by pre-crisis sales, and b) cumulative advertisement expenses in t and $t+1$ normalised by pre-crisis sales as dependent variables augmented with interactions of firm level characteristics capturing the above channels. The result remains similar in the presence of additional interactions. Innovative firms in industries with a high scope for product differentiation react to a severe negative shock by spending more on product differentiation during the recession, however this is not true in industries with homogenous products.

7 Conclusion

The main finding of this paper is that the *ex-ante* R&D intensity of a firm has a positive effect on its growth in bad times. Using firm level data for Spain, I find that R&D firms in industries that were exogenously severely hit by the crisis, as proxied by an export shock in the empirical analysis, did relatively well. I find that the key mechanism that makes R&D intensive firms suffer lesser is that they are able to change their products in response to external changes in their environment. Specifically, I find that R&D intensive firms continue to invest in capital goods for product improvement and increase their advertising expenses when hit with a demand shock.

This research has important policy implications for managers, firms and governments deciding how much to invest in R&D. Moreover, questions regarding R&D subsidies and patent protection have been prominent policy issues in developed countries in the aftermath of the Great Recession (Aghion et al., 2014). This research does not shed light on whether governments or firms should increase R&D spending *during* a crisis. It suggests that firms that are R&D intensive prior to the crisis are capable of handling a crisis better

impact of *local demand shock* during the Great Recession of 2008, thus suggesting that *ex-ante* exporters could be resilient to the recession because they could 'vent out' relatively easily. The results in column (3) of Table 15 shows that firms with high export intensity prior to the crisis did not perform relatively better in sectors hit severly during the crisis, as measured by the demeaned decline in exports at industry level. Given the measure of Shock, it is not surprising that export intensive firms do not show superior performance in sectors that experienced a large decline in exports.

than other firms. Thus R&D expenditure *today* might act as a stabilising tool in turbulent times, and this should be taken into consideration when evaluating investment alternatives and policy options.

This paper is one of the first to empirically evaluate the relationship between firm growth and R&D during a crisis, adding another string to the roles of R&D. There are many directions for future work. First, it is important to understand the channels that allow R&D firms to be more resilient to demand shocks. While the work finds that R&D firms are changing their product portfolio in times of crises, it does not shed light on the exact form of change in products, such as design, functionality, material or components. This requires more detailed data on products added and dropped, resource allocation by product, markets the firms participates in etc. Second, comparative evidence from other countries can give us a deeper understanding of macro structures that help R&D firms to be resilient in bad times. A third issue left unaddressed is the general equilibrium effect of this channel of resilience to demand shocks. The framework does not offer an answer to the aggregate effect of higher R&D spending by all firms.

Tables and Figures

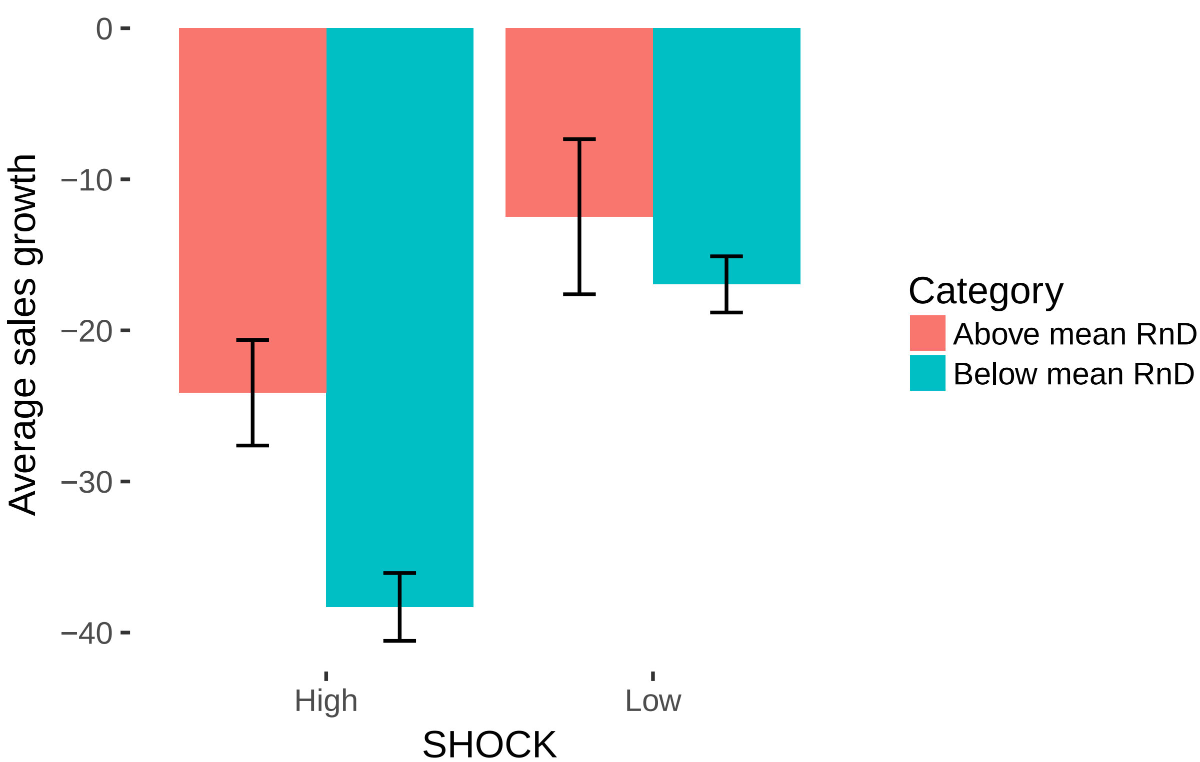
Table 1: Summary statistics

Independent variables	Mean	Median	SD	Observed
Employment	231.80	50.00	761.47	3872
Age	31.15	25.00	22.05	3870
RnD to sales ratio	0.69	0.00	2.01	3871
Export to sales ratio	18.78	3.76	26.65	3866
TFP	-1.69	-0.73	3.04	3847
Product innovation	0.18	0.00	0.39	3872
Process innovation	0.35	0.00	0.48	3872
No. of product innovations	1.24	0.00	8.84	3872
No. of products	1.17	1.00	0.46	3872
No. of international markets	0.77	0.00	1.05	3872
Total patents	0.51	0.00	6.39	3872
Skilled employees ratio	5.85	3.60	8.51	3860
Belongs to a group	0.35	0.00	0.48	3859
Short-term debt to sales ratio	41.55	30.42	79.47	3872
Foreign ownership	14.12	0.00	33.96	3872
Leverage	4.67	1.36	26.10	3746
Asset tangibility	87.04	95.94	18.54	3867
Temporary workers ratio	12.07	6.35	16.27	3872
Part-time workers ratio	0.03	0.00	0.06	3872
Employee training to sales ratio	0.00	0.00	0.01	3871

Dependent variables	Mean	Median	SD	Observed
Sales growth (two year difference)	-28.45	-23.98	41.85	3090
Employment growth (two year difference)	-10.54	-10.65	34.57	3090
Investment in capital goods (cumulated for two years) to sales ratio	7.70	3.18	30.34	3057
Value-added growth (two year difference)	10.04	-17.74	509.60	3090
Profit (cumulated for two years) to sales ratio	10.10	9.61	21.81	3061
Product improvement cost (cumulated for two years) to sales ratio	1.46	0.00	6.06	3055
Advertisement expenses (cumulated for two years) to sales ratio	1.77	0.36	4.79	3061
Change in output prices (two year difference)	0.48	0.00	8.16	3061
Change in input prices (two year difference)	5.15	4.00	9.62	3061
Change in marginal cost (two year difference)	1.44	0.98	13.96	3061
Change in markups (two year difference)	0.79	-0.03	16.99	3061

Note: Note: The table presents summary statistics for the sample of Spanish manufacturing firms used in the baseline regression in table 2. Independent variable data is pooled for years 2007 and 2008. Dependent variables measured as two year differences from $t-1$ to $t+1$ are pooled for difference over 2007-09, and 2008-10. Variables that are cumulated over t and $t+1$ and normalised by sales in $t-1$ are pooled for cumulation over 2008-09 and 2009-10.

Figure 1: Change in Sales by Shock and R&D



Note: The figure uses data for sales growth of firms measured over 2007-09 and 2008-10, winsorised at 0.5% on both tails. Firms are divided into two groups, those that were hit by a below mean shock (labelled High), as measured by detrended decline in exports during the crisis, and above mean shock (labelled Low). Within each of these categories, firms are divided into those with above mean R&D intensity in the sample, and below mean R&D intensity. The mean sales growth is depicted by the coloured bars, and the black lines represent 99% confidence intervals.

Table 2: R&D and firm growth: Baseline regressions

	Dependent variable: Sales growth (Two year difference)			
	OLS	*OLS*	*OLS*	*IV*
	(1)	(2)	(3)	(4)
R&D$_{t-1}$	2.321***	-0.546	-0.078	-0.431
	(0.341)	(1.388)	(1.066)	(1.129)
Shock	-0.761^{***}	-0.814^{**}		
	(0.062)	(0.318)		
R&D$_{t-1}$*Shock		0.148**	0.088**	0.106**
		(0.063)	(0.045)	(0.050)
Industry year FE			*Yes*	*Yes*
Location FE			*Yes*	*Yes*
Firm controls			*Yes*	*Yes*
Weak instruments (F-stat)				28.09
Observations	3,058	3,058	3,038	3,038
R^2	0.229	0.059	0.240	0.240

Note: The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as percentage change from 2006-07 to 2008-09, detrended by previous three year growth rate calculated as the difference in two year rolling mean of log of export value. Column (3) and (4) contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level in columns (2), (3), and (4), and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 3: Placebo test: Pre-crisis years

	Dependent variable: Sales growth (Two year difference)			
	(1)	(2)	(3)	(4)
R&D	1.321***	1.355**	0.894***	0.360
	(0.259)	(0.687)	(0.205)	(0.480)
R&D*Shock		−0.009		
		(0.024)		
R&D*GFC			0.802**	1.794**
			(0.353)	(0.704)
R&D*Year-wise shock				−0.024
				(0.017)
R&D*GFC*Year-wise shock				0.068*
				(0.036)
Industry by year FE	*Yes*	*Yes*	*Yes*	*Yes*
Plant location FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls		*Yes*	*Yes*	*Yes*
Observations	2,328	2,286	8,395	8,395
R^2	0.089	0.096	0.284	0.285

Note: The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. In columns (1) and (2), data is pooled for growth over 2003-2005 and 2004-06. Growth is winsorised at 0.5% on both tails. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$, that is 2003 and 2004 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous five year growth rate. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Year-wise shock is measured as the year-on-year change in log value of exports. GFC is a dummy equal to 1 for $t \in 2008, 2009$. Standard errors are clustered at industry level in columns (2), (3) and (4), and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 4: R&D and Survival during recession

	Dependent variable: Survival		
	Probit	*IV*	*Placebo test*
	(1)	(2)	(3)
R&D*Shock	0.005**	0.001**	0.004
	(0.002)	(0.0003)	(0.004)
Industry year FE	*Yes*	*Yes*	*Yes*
Plant location FE	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*
Observations	3,395	3,395	2,366
R^2		0.078	
Log Likelihood	-1,053.901		-274.596
Akaike Inf. Crit.	2,227.801		669.193

Note: The dependent variable in is a dummy variable equal to one for firms that are observable from $t1$ to $t+1$, and 0 for firms that are observable in $t1$ but not in t or $t+1$. R&D is firm level R&D as a percentage of sales, measured at $t-1$. In columns (1) and (2), $t \in 2007, 2008$, and in column (3) $t \in 2003, 2004$. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous five year growth rate. All columns control for log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 5: Alternative firm level outcomes

	Dependent variable: At two year horizon			
	Value added	Profit margin	Employment growth	Capital expenditure
	(1)	(2)	(3)	(4)
R&D*Shock	0.146**	−0.028	0.013	0.023***
	(0.064)	(0.046)	(0.026)	(0.009)
Industry-year FE	*Yes*	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3,039	3,041	3,038	3,041
R^2	0.084	0.098	0.131	0.112

Note: The dependent variable in column (1) is difference in log value of value added from $t-1$ to $t+1$. Column (2) dependent variable is cumulative profit over t and $t+1$ divided by sales in $t-1$. Column (3) is employment growth measured as difference in log value of number of employees from $t-1$ to $t+1$. Dependent variable in column (4) is cumulative investment in capital goods in t and $t+1$ divided by sales in $t-1$. Dependent variable in Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous five year growth rate. Cumulative variables are cumulated for 2008-2009, and 2009-2010. All columns control for log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Column (2) controls for investment to sales ratio in $t-1$, and column (4) controls for profit to sales ratio in $t-1$. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 6: Alternative measurement of Shock variable

	Dependent variable: Sales Growth at a two year horizon					
	(1)	(2)	(3)	(4)	(5)	(6)
R&D *Number of firms	0.440	0.464				
	(0.277)	(0.286)				
R&D *Shock		0.089*		0.087*		0.086**
		(0.046)		(0.046)		(0.043)
R&D *Financial dependence			0.084	0.076		
			(0.133)	(0.120)		
R&D *Industry output					−0.038	−0.030
					(0.084)	(0.083)
Industry year FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,038	3,038	3,038	3,038	3,038	3,038
R^2	0.239	0.240	0.239	0.240	0.239	0.240

Note: The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. Number of firms is the percentage decline in number of active firms at region level in Spain. I invert this value to interpret a larger decline as a bigger shock. Financial dependence is a measure of external financial dependence following Rajan and Zingales (1998) at industry level. Industry output is the percentage decline in gross value added at an industrial level. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 7: Using percentage of skilled workers as a proxy for R&D

	Dependent variable: Sales Growth (Two year difference)		
	Baseline	IV	Placebo
	(1)	(2)	(3)
Skilled workers	−0.189	−0.642	0.273
	(0.197)	(0.438)	(0.198)
Skilled workers*Shock	0.040***	0.066***	0.0004
	(0.011)	(0.021)	(0.011)
Industry Year FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Observations	3,029	3,029	2,255
R^2	0.244	0.243	0.091

Note: The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. Skilled workers are the proportion of graduates and engineers in total employment measured in 2006. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous five year growth rate. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 8: Successful firms

	Dependent variable: Sales growth (Two year difference)				
	(1)	(2)	(3)	(4)	(5)
TFP*Shock	0.048				
	(0.121)				
Size*Shock		-0.047			
		(0.039)			
Salesgr_{t-1}*Shock			-0.0004		
			(0.003)		
Product innovation*Shock				-0.149	
				(0.187)	
Process innovation*Shock					0.094
					(0.103)
RnD intensity*Shock	0.091^{**}	0.092^{**}	0.090^{*}	0.090^{**}	0.084^{*}
	(0.043)	(0.044)	(0.047)	(0.041)	(0.045)
Industry-year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3,038	3,038	2,486	3,038	3,038
R^2	0.240	0.240	0.249	0.240	0.240

Note: The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. Total factor productivity calculation is discussed in appendix B. Size is the log of the number of employees. Salesgr is the sales growth of a firm in $t-1$. Process innovation is a categorical variable for whether the firm reported a process innovation. Product innovation is a categorical variable for whether the firm reported a product innovation. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 9: R&D spending during the crisis

	Dependent variable:	
	$\text{R\&D}_{t+1,t}$	$\text{R\&D}_{t+2,t}$
	(1)	(2)
R&D	0.483^{***}	0.649^{*}
	(0.129)	(0.369)
R&D *Shock	0.015^{**}	0.045^{**}
	(0.006)	(0.020)
Industry Year FE	Yes	Yes
Location FE	Yes	Yes
Observations	3,438	3,034
R^2	0.569	0.531

Note: The dependent variable is firm R&D expenditure measured at t in column (1), and cumulated over t and $t+1$ in column (2), as a percentage of pre-crisis sales. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 10: By degree of product differentiation

	Dependent variable: Sales Growth at two year horizon					
	Differentiated pdts	Homogenous pdts	R&D intensive	Not R&D intensive	High tech sectors	Low tech sectors
	(1)	(2)	(3)	(4)	(5)	(6)
R&D *Shock	0.198***	0.027	0.159**	0.062	0.129**	0.001
	(0.070)	(0.052)	(0.076)	(0.054)	(0.055)	(0.061)
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,473	1,565	1,167	1,871	827	2,211
R^2	0.168	0.251	0.213	0.274	0.218	0.266

Note: Column (1) and (2) are split using the RAUCH classification for identifying sectors with differentiated products and those with homogenous products. Using R&D intensity of industries from EU KLEMS, sample is split in columns (3) and (4) by median of industry R&D intensity. Using OECD definition of whether an industry is technology intensive or not, sample is split in columns (5) and (6). The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 11: Expenditure on product improvement and advertisement

	At a two-year horizon			
	Product improvement investment		Advertisement expenses	
	Differentiated pdts	Homogenous pdts	Differentiated pdts	Homogenous pdts
	(1)	(2)	(3)	(4)
R&D *Shock	0.040**	0.002	0.005***	−0.0005
	(0.019)	(0.004)	(0.001)	(0.006)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	
Observations	1,483	1,556	1,483	1,558
R^2	0.078	0.076	0.463	0.755

Note: Sample is split between columns (1) and (2), and columns (3) and (4) using the RAUCH classification for identifying sectors with differentiated products and those with homogenous products. The dependent variable is cumulative expenditure on product improvement in t and $t+1$ normalised by pre-crisis sales in columns (1) and (2) , and cumulative advertisement expenses in t and $t+1$ normalised by pre-crisis sales in columns (3) and (4). R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. Columns (1) and (2) control for expenditure on product improvement as a percentage of sales in $t-1$, and columns (3) and (4) control for advertisement expenses as a percentage of sales in $t-1$. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 12: Change in prices, marginal cost, and markup

	Dependent variable: At a two-year horizon			
	InputPrice	OutputPrice	Marginal cost	Markup
	(1)	(2)	(3)	(4)
R&D *Shock	0.004	0.005	0.032***	−0.032**
	(0.011)	(0.005)	(0.012)	(0.015)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	3,010	3,009	3,028	3,028
R^2	0.065	0.061	0.106	0.099

Note: The dependent variable in column (1) is percentage change in input prices, column (2) is percentage change in output price, column (3) is percentage change in marginal cost, and column (4) is percentage in markup from $t-1$ to $t+1$. Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 13: Financing constraints

	Dependent variable: Sales Growth (Two year difference)				
	(1)	(2)	(3)	(4)	(5)
GROUP*Shock	0.021				
	(0.153)				
Short-term debt*Shock		0.006^{***}			
		(0.002)			
Foreign Own*Shock			0.003^{**}		
			(0.001)		
Leverage*Shock				-0.001	
				(0.003)	
Asset tangibility*Shock					-0.002
					(0.003)
R&D*Shock	0.097^{**}	0.082^{**}	0.095^{**}	0.101^{**}	0.096^{**}
	(0.046)	(0.039)	(0.043)	(0.046)	(0.044)
Industry-year FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Observations	3,011	3,020	3,020	2,952	3,020
R^2	0.231	0.236	0.231	0.235	0.230

Note: The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. GROUP is equal to 1 for firms that belong to a business group. Short term debt is the ratio of debt due to mature within one year and sales. Foreign Ownership is the percentage of foreign shareholding in a firm. Leverage is the ratio of total debt to stockholder's equite in a firm. Asset tangibility is the ratio of fixed assets in total assets of a firm. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 14: Trapped factors mechanism

	Dependent variable: Sales Growth (Two year difference)		
	(1)	(2)	(3)
Temporary staff*Shock	-0.005		
	(0.005)		
Part-time staff*Shock		-0.907	
		(1.048)	
Employee training expenses*Shock			29.601
			(71.579)
R&D *Shock	0.094^{**}	0.098^{**}	0.097^{**}
	(0.046)	(0.045)	(0.044)
Industry Year FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Observations	3,020	3,020	3,020
R^2	0.232	0.230	0.230
Adjusted R^2	0.216	0.215	0.214
Residual Std. Error	32.365	32.396	32.399
F Statistic	14.642^{***}	14.523^{***}	14.511^{***}

Note: The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. Data is pooled for growth over 2007-2009 and 2008-10. Growth is winsorised at 0.5% on both tails. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. Temporary staff is the ratio of temporary salaried staff and total staff measured at $t-1$. Part-time staff is the ratio of part-time salaried regular workers and total staff measured at $t-1$. Employment training expenses is the ratio of total external training expenses and sales measured at $t-1$. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls measured at $t-1$. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 15: Diversity of inputs

	Dependent variable: Sales growth at a two year horizon			
	(1)	(2)	(3)	(4)
No. of products*Shock	0.061			
	(0.133)			
No. of international markets*Shock		−0.037		
		(0.045)		
Export Intensity*Shock			0.002	
			(0.003)	
Product customisation*Shock				-0.418^{***}
				(0.079)
R&D *Shock	0.089^{**}	0.093^{**}	0.085^{*}	0.092^{**}
	(0.045)	(0.043)	(0.047)	(0.044)
Industry Year FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	3,038	3,038	3,038	3,027
R^2	0.242	0.241	0.240	0.243

Note: The dependent variable is firm real sales growth measured by deflating firm sales with firm level prices, and growth measured from $t-1$ to $t+1$. In columns (1) and (2), data is pooled for growth over 2003-2005 and 2004-06. Growth is winsorised at 0.5% on both tails. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2003 and 2004 for the two cross-sections. No. of products is the number of products at CNAE-09 three-digit produced by a firm. Number of international markets is the markets with international scope. Export intensity is export sales as a percentage of total sales. Product customisation is a dummy equal to one if a firms' response to whether its products are mostly standardised is 'Low'. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Year-wise shock is measured as the year-on-year change in log value of exports. GFC is a dummy equal to 1 for $t \in 2008, 2009$. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

References

Abadie, A., S. Athey, G. W. Imbens, and J. Wooldridge (2017). When should you adjust standard errors for clustering? Technical report, National Bureau of Economic Research Working Paper No. 24003.

Ackerberg, D. A., K. Caves, and G. Frazer (2015). Identification properties of recent production function estimators. *Econometrica 83*(6), 2411–2451.

Aghion, P., U. Akcigit, and P. Howitt (2014). Chapter 1 - what do we learn from schumpeterian growth theory? In P. Aghion and S. N. Durlauf (Eds.), *Handbook of Economic Growth*, Volume 2 of *Handbook of Economic Growth*, pp. 515 – 563. Elsevier.

Aghion, P., N. Bloom, B. Lucking, R. Sadun, and J. Van Reenen (2017). Turbulence, firm decentralization and growth in bad times. Technical report, National Bureau of Economic Research Working Paper No. 23354.

Aghion, P. and G. Saint-Paul (1998). Virtues of bad times interaction between productivity growth and economic fluctuations. *Macroeconomic Dynamics 2*(03), 322–344.

Alfaro, L. and M. X. Chen (2012). Surviving the global financial crisis: foreign ownership and establishment performance. *American Economic Journal: Economic Policy 4*(3), 30–55.

Almunia, M., D. Lopez-Rodriguez, P. Antras, and E. Morales (2017). Venting out: Exports during a domestic slump. Technical report, Mimeo:https://scholar.harvard.edu/antras/publications/venting-out-exports-during-domestic-slump.

Alviarez, V., J. Cravino, and A. A. Levchenko (2017). The growth of multinational firms in the great recession. *Journal of Monetary Economics 85*, 50–64.

Archibugi, D., A. Filippetti, and M. Frenz (2013). Economic crisis and innovation: Is destruction prevailing over accumulation? *Research Policy 42*(2), 303–314.

Argente, D., M. Lee, and S. Moreira (2018a). How do firms grow? the life cycle of products matters. Technical report, Available at SSRN: https://ssrn.com/abstract=3163195.

Argente, D., M. Lee, and S. Moreira (2018b). Innovation and product reallocation in the great recession. *Journal of Monetary Economics 93*, 1–20.

Behrens, K., G. Corcos, and G. Mion (2013). Trade crisis? what trade crisis? *Review of economics and statistics 95*(2), 702–709.

Bentolila, S., P. Cahuc, J. J. Dolado, and T. Le Barbanchon (2012). Two-tier labour markets in the great recession: France versus spain. *The Economic Journal 122*(562), F155–F187.

Bernard, A. B. and T. Okubo (2016). Product switching and the business cycle. Technical report, National Bureau of Economic Research Working Paper No. 22649.

Bloom, N. (2007). Uncertainty and the dynamics of r&d. *The American Economic Review 97*(2), 250.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2013). Does management matter? evidence from india. *The Quarterly Journal of Economics 128*(1), 1–51.

Bloom, N., P. M. Romer, S. J. Terry, and J. V. Reenen (2013). A trapped-factors model of innovation. *The American Economic Review 103*(3), 208–213.

Bricongne, J.-C., L. Fontagné, G. Gaulier, D. Taglioni, and V. Vicard (2012). Firms and the global crisis: French exports in the turmoil. *Journal of international Economics 87*(1), 134–146.

Caballero, R. J. and M. L. Hammour (1994). The cleansing effect of recessions. *The American Economic Review 84*(5), 1350–1368.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Clark, K. B. and Z. Griliches (1984). Productivity growth and R&D at the business level: Results from the PIMS data base. In *R&D, Patents, and Productivity*, pp. 393–416. University of Chicago Press.

Cohen, W. M. and D. A. Levinthal (1989). Innovation and learning: the two faces of r & d. *The economic journal 99*(397), 569–596.

Collard-Wexler, A. and J. De Loecker (2016). Production function estimation with measurement error in inputs. Technical report, National Bureau of Economic Research Working Paper No. 22437.

De Loecker, J. and F. Warzynski (2012). Markups and firm-level export status. *American economic review 102*(6), 2437–71.

Doraszelski, U. and J. Jaumandreu (2013). R&d and productivity: Estimating endogenous productivity. *Review of Economic Studies 80*(4), 1338–1383.

Eckel, C. and J. P. Neary (2010). Multi-product firms and flexible manufacturing in the global economy. *The Review of Economic Studies 77*(1), 188–217.

Fajgelbaum, P., G. M. Grossman, and E. Helpman (2011). Income distribution, product quality, and international trade. *Journal of political Economy 119*(4), 721–765.

Fort, T. C., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2013). How firms respond to business cycles: The role of firm age and firm size. *IMF Economic Review 61*(3), 520–559.

Foster, L., C. Grim, and J. Haltiwanger (2016). Reallocation in the great recession: Cleansing or not? *Journal of Labor Economics 34*(S1 Part 2), S293–S331.

García-Santana, M., E. Moral-Benito, J. Pijoan-Mas, and R. Ramos (2016). Growing like spain: 1995-2007. Technical report, Banco de Espana Working Paper No. 1609.

Garcia-Vega, M. (2006). Does technological diversification promote innovation?: An empirical analysis for european firms. *Research policy 35*(2), 230–246.

Garicano, L. and C. Steinwender (2016). Survive another day: Using changes in the composition of investments to measure the cost of credit constraints. *Review of Economics and Statistics 98*(5), 913–924.

Geroski, P. A. (1998). An applied econometrician's view of large company performance. *Review of Industrial Organization 13*(3), 271–294.

Giroud, X. and H. M. Mueller (2017). Firm leverage, consumer demand, and employment losses during the great recession. *The Quarterly Journal of Economics 132*(1), 271–316.

Gopinath, G., Ş. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017). Capital allocation and productivity in south europe. *The Quarterly Journal of Economics 132*(4), 1915–1967.

Griffith, R., S. Redding, and J. Van Reenen (2003). R&d and absorptive capacity: theory and empirical evidence. *The Scandinavian Journal of Economics 105*(1), 99–118.

Guadalupe, M., O. Kuzmina, and C. Thomas (2012). Innovation and foreign ownership. *The American Economic Review 102*(7), 3594.

Hall, B. H. and J. Lerner (2010). The financing of r&d and innovation. In *Handbook of the Economics of Innovation*, Volume 1, pp. 609–639. Elsevier.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society 57*(2), 357–384.

Hombert, J. and A. Matray (2018). Can innovation help us manufacturing firms escape import competition from china? *The Journal of Finance 73*(5), 2003–2039.

Jaumandreu, J. and S. Lin (2018). Pricing under innovation. Technical report, Mimeo:https://open.bu.edu/handle/2144/29255.

King, R. G. and S. T. Rebelo (1999). Resuscitating real business cycles. *Handbook of macroeconomics 1*, 927–1007.

Koren, M. and S. Tenreyro (2013). Technological diversification. *American Economic Review 103*(1), 378–414.

Kugler, M. and E. Verhoogen (2011). Prices, plant size, and product quality. *The Review of Economic Studies 79*(1), 307–339.

Lazear, E. P., K. L. Shaw, and C. Stanton (2016). Making do with less: working harder during recessions. *Journal of Labor Economics 34*(S1), S333–S360.

Nanda, R. and T. Nicholas (2014). Did bank distress stifle innovation during the great depression? *Journal of Financial Economics 114*(2), 273–292.

Nonaka, I., R. Toyama, and A. Nagata (2000). A firm as a knowledge-creating entity: a new perspective on the theory of the firm. *Industrial and corporate change 9*(1), 1–20.

Organisation for Economic Co-operation and Development (2011). Isic rev. 3 technology intensity definition. Technical report, OECD Directorate for Science, Technology and Industry.

Rajan, R. G. and L. Zingales (1998). Financial dependence and growth. *The American Economic Review 88*(3), 559–586.

Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of international Economics 48*(1), 7–35.

Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy 98*(5, Part 2), S71–S102.

Romer, P. M. (1994). The origins of endogenous growth. *Journal of Economic perspectives 8*(1), 3–22.

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*, Volume 55. Transaction publishers.

Sharma, S. and H. Winkler (2017). The labor market effects of financial crises: The role of temporary contracts in central and western europe. Technical report, World Bank Policy Research Working Paper.

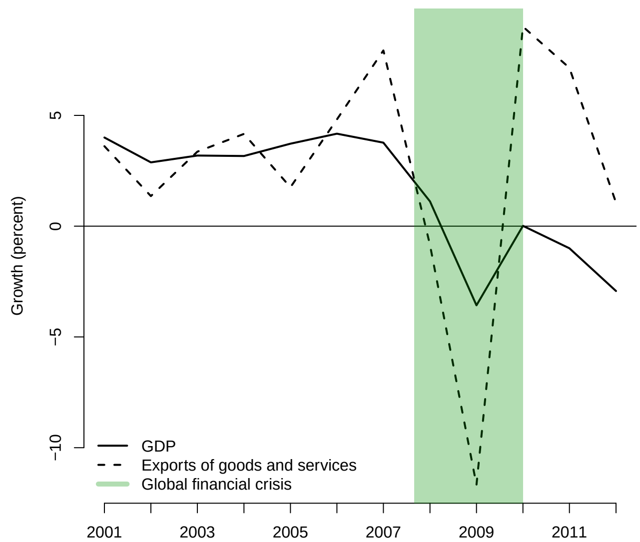
Teece, D. and G. Pisano (1994). The dynamic capabilities of firms: an introduction. *Industrial and corporate change 3*(3), 537–556.

Wang, C. L. and P. K. Ahmed (2007). Dynamic capabilities: A review and research agenda. *International journal of management reviews 9*(1), 31–51.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic management journal 24*(10), 991–995.

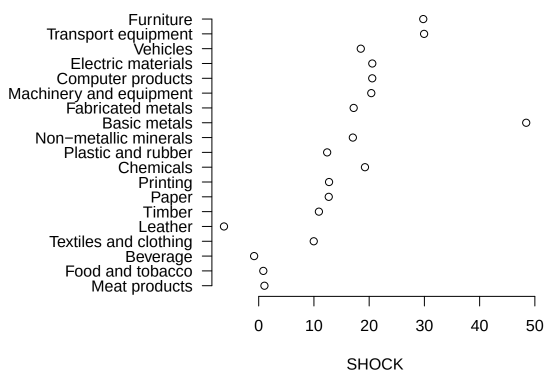
A Appendix: Additional Tables

Figure A.2: Spain: Aggregate performance indicators



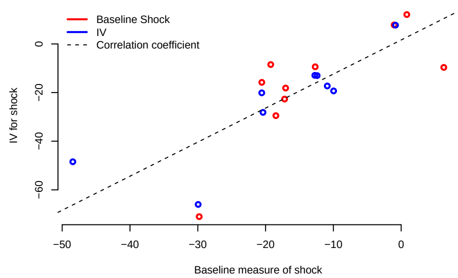
Note: The data is from World Bank's databank, World Development indicators. Both series are measured at constant 2010 USD.

Figure A.3: Export growth by sector



Note: The figure plots export growth during the crisis for 19 industry groups in the sample. Export growth on the y-axis is the difference between the log of average export value for 2006-2007, and for 2008-2009 for each three-digit NACE industry. This value is demeaned with the average growth rate, calculated as difference between two year rolling average of log of export value, for pre-crisis years for each industry.

Figure A.4: Correlation between baseline measure and IV for crisis intensity



Note: The figure shows the correlation between export growth for Spain during the crisis on the x-axis, and export growth for the US on the y-axis for 19 industry groups.

Table A1: Summary statistics by R&D status

	No R&D	R&D
Sales (million euros)	23.42	180.25
Employment (number)	90.56	490.57
Value of exports (million euros)	4.73	74.98
TFP ()	0.15	0.22
Age (years)	26.6	36.57
Sales growth (cumulated over 3 years)	-21.83	-12.94
Observations	2503	1362

Note: The table presents summary statistics for the sample of Spanish manufacturing firms used in the baseline regression in table 2. Independent variable data is pooled for years 2007 and 2008. Dependent variables measured as two year differences from $t-1$ to $t+1$ are pooled for difference over 2007-09, and 2008-10. Variables that are cumulated over t and $t+1$ and normalised by sales in $t-1$ are pooled for cumulation over 2008-09 and 2009-10.

Table A2: Changing key variables

	Dependent variable: Sales Growth (two year difference)					
	Sales Growth (one year difference)	Without winsorisation	With R&D stock	With R&D in t-5	Shock without detrending	More firm controls
	(1)	(2)	(3)	(4)	(5)	(6)
R&D*Shock	0.087***	0.081*				0.075*
	(0.024)	(0.043)				(0.044)
R&D stock*Shock			2.589**			
			(1.206)			
R&D(t-5)*Shock				0.099*		
				(0.056)		
R&D*Shock (no detrending)					0.103**	
					(0.046)	
Industry-year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	
Location FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	
Observations	3,407	3,070	3,038	1,567	3,038	3,027
R^2	0.244	0.214	0.236	0.246	0.240	0.255

Note: The dependent variable in column (1) is a one-year difference in real sales growth, in column (2) two year difference in real sales growth is not winsorised, and in columns (3)-(6) the dependent variable is firm real sales growth measured from $t-1$ to $t+1$. Following Hombert and Matray (2018), column (3) uses a measure of firm innovative effort by calculating R&D stock as the sum of previous R&D expenses of a firm, depreciated annually at 15%, as a percentage of sales in $t-1$. In column (4), I use the five year lagged value of R&D intensity. In column (5), the crisis intensity measure is growth in exports without detrending it. Column (6) controls for total patents of a firm, whether or not it had a product, process, management or organisational innovation at $t-1$, its import intensity, asset tangibility, whether it is part of a group, its short-term debt as a ratio of its sales, and its self reported market share and whether it thinks the markets it is participating in are expanding, stable or in decline. Column (6) includes an interaction for firms observed from 2008-10. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table A3: RAUCH classification of industry groups

Differentiated industries	Homogenous industries
Non-metallic minerals	Meat products
Fabricated metals	Plastic and rubber
Machinery and equipment	Basic metals
Computer products	Furniture
Electric materials	Food and tobacco
Transport equipment	Beverage
Textiles and clothing	Paper
Leather	Vehicles
Timber	Printing
	Chemicals

Table A4: Product and process innovation

	Dependent variable:		
	Product inn	No. of Prod inn	Process inn
	(1)	(2)	(3)
R&D	0.015	0.028	0.009
	(0.014)	(0.030)	(0.021)
R R&D*Shock	−0.0003	−0.001	0.0004
	(0.001)	(0.001)	(0.001)
Industry-year FE	Yes	Yes	Yes
Plant location FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Observations	3,041	3,041	3,041
R^2	0.386	0.442	0.383
Adjusted R^2	0.374	0.431	0.371
Residual Std. Error	0.343	0.655	0.661
F Statistic	31.255***	39.417***	30.870***

Note: The dependent variable in column (1) is a categorical variable for whether a firm had a product innovation in t or $t+1$, in column (2) it is the log of cumulated number of total number of product innovations in t and $t+1$ plus one, and in column (3) it is a categorical variable for whether a firm had a process innovation in t or $t+1$. R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Column (1) also includes a control for whether firm i had a product innovation in $t-1$, column (2) controls for log of number of product innovations in $t-1$ plus one, and column (3) controls for whether firm i had a process innovation in $t-1$. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table A5: Expenditure on product improvement and advertisement: By product customisation

	At a two-year horizon			
	Product improvement investment		Advertisement expenses	
	Customised pdts	Standardised pdts	Customised pdts	Standardised pdts
	(1)	(2)	(3)	(4)
R&D	−0.430	−0.046	−0.034	0.111
	(0.322)	(0.046)	(0.043)	(0.108)
R&D*Shock	0.032*	0.001	0.004**	−0.002
	(0.018)	(0.003)	(0.002)	(0.007)
Industry Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,300	1,728	1,300	1,730
R^2	0.099	0.072	0.439	0.747

Note: Sample is split between columns (1) and (2), and columns (3) and (4) using firm reported value of whether their products are customised or standardised. The dependent variable is cumulative expenditure on product improvement in t and t+1 normalised by pre-crisis sales in columns (1) and (2) , and cumulative advertisement expenses in t and t+1 normalised by pre-crisis sales in columns (3) and (4). R&D is firm level R&D as a percentage of sales, measured at $t-1$, that is 2007 and 2008 for the two cross-sections. *Shock* is industry level export growth measured as change from 2006-07 to 2008-09, detrended by previous three year growth rate. Columns (1) and (2) control for expenditure on product improvement as a percentage of sales in $t-1$, and columns (3) and (4) control for advertisement expenses as a percentage of sales in $t-1$. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table A6: Coefficient for R&D*Shock when controlling for additional firm characteristics interacted with Shock

	Product improvement investment		Advertisement expenses	
	Differentiated	Homogenous	Differentiated	Homogenous
	(1)	(2)	(3)	(4)
TFP	0.039 (0.018) *	0.003 (0.004)	0.005 (0.001) ***	0.001 (0.005)
Size	0.041 (0.021) *	0.003 (0.004)	0.006 (0.002) ***	0 (0.006)
Salesgr_{t-1}	0.004 (0.002) *	0.003 (0.005)	0.006 (0.001) ***	0.001 (0.006)
Product inn	0.041 (0.019) *	0.005 (0.005)	0.005 (0.002) **	0.003 (0.007)
Process inn	0.042 (0.019) *	0.005 (0.006)	0.005 (0.001) ***	0.001 (0.007)
GROUP	0.04 (0.019) *	0.002 (0.004)	0.005 (0.001) ***	0 (0.006)
Short-term debt	0.04 (0.019) *	0.002 (0.004)	0.005 (0.001) ***	-0.001 (0.006)
Foreign Own	0.044 (0.022) *	0.002 (0.004)	0.006 (0.002) ***	-0.001 (0.005)
Leverage	0.024 (0.007) **	0.002 (0.004)	0.005 (0.001) ***	0 (0.006)
Asset tangibility	0.039 (0.017) *	0.002 (0.004)	0.005 (0.002) **	-0.001 (0.005)
Temporary staff	0.04 (0.018) *	0.002 (0.004)	0.005 (0.001) ***	-0.001 (0.006)
Part-time staff	0.041 (0.019) *	0.002 (0.004)	0.005 (0.001) ***	0 (0.006)
Employee training expenses	0.04 (0.019) *	0.002 (0.004)	0.005 (0.001) ***	0 (0.006)
No. of products	0.04 (0.019) *	0.002 (0.004)	0.005 (0.001) ***	0 (0.006)
No. of international markets	0.04 (0.019) *	0.003 (0.004)	0.005 (0.001) ***	0 (0.006)
Export intensity	0.041 (0.019) *	0.003 (0.004)	0.005 (0.001) ***	0 (0.006)
Product customisation	0.04 (0.018) *	0.002 (0.005)	0.005 (0.002) ***	-0.001 (0.006)

Note: Each cell shows the coefficient for the interaction of R&D intensity in $t-1$ and Shock from a different regression. The regressions differ in the independent variables included such that each regression is the baseline regression described in equation 2 augmented with an interaction of a firm characteristic and Shock. Row names in the table show the firm characteristic that is measured in $t-1$ and added as an interaction term in the regression. Standard errors are clustered at industry level and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance. Sample is split between columns (1) and (2), and columns (3) and (4) using the RAUCH classification for identifying sectors with differentiated products and those with homogenous products. The dependent variable is cumulative expenditure on product improvement in t and $t+1$ normalised by pre-crisis sales in columns (1) and (2) , and cumulative advertisement expenses in t and $t+1$ normalised by pre-crisis sales in columns (3) and (4). Total factor productivity calculation is discussed in appendix B. Size is the log of the number of employees. Salesgr is the sales growth of a firm in t 1. Process innovation is a categorical variable for whether the firm reported a process innovation. Product innovation is a categorical variable for whether the firm reported a product innovation. GROUP is equal to 1 for firms that belong to a business group. Short term debt is the ratio of debt due to mature within one year and sales. Foreign Ownership is the percentage of foreign shareholding in a firm. Leverage is the ratio of total debt to stockholders equite in a firm. Asset tangibility is the ratio of fixed assets in total assets of a firm. Temporary staff is the ratio of temporary salaried staff and total staff. Part-time staff is the ratio of part-time salaried regular workers and total staff. Employment training expenses is the ratio of total external training expenses and sales. No. of products is the number of products at CNAE-09 three-digit produced by a firm. Number of international markets is the markets with international scope. Export intensity is export sales as a percentage of total sales. Product customisation is a dummy equal to one if a firms response to whether its products are mostly standardised is Low. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls.

Table A7: Definition of key variables

Variable (unit)	Definition
Sales	The sales of goods, the sales of transformed products (finished and half-finished), the provision of services and other sales (packages, packaging, byproducts and waste), rappels and sales returns excluded. In Euros.
Value added	The sum of the sales, the variation in stocks and other management income, minus the purchases and external services. In Euros.
Total employment	Total personnel employed at the company on December 31st. This includes both salaried and non-salaried staff.
Investment	The sum of the purchases of information processing equipment, technical facilities, machinery and tools, rolling stock and furniture, office equipment and other tangible fixed assets. It does not include investment into land and buildings. In Euros.
R&D expenses	Total expenses in internal and external R&D activities during the year. In Euros.
Gross operating margin	Measurement of the company's profitability, defined as the percentage which the sum of the sales, the change in stocks and other current management income minus the purchases, external services and labor costs, represent on total sales plus the change in stocks of them and other current management income.
Age	Number of years since the year of incorporation

B Appendix: Data description

B.1 Mapping NACE to SITC

Firms in ESEE are classified into industry groups based on the statistical classification of economic activities in the European Community, abbreviated as NACE (Revision 2), which is derived from ISIC, but is more detailed that ISIC at lower levels. There are 20 unique industry groups in ESEE with a one-to-one mapping to 2-digit NACE classification. To link firm level data to the baseline measure of severity of crisis at industry level, detrended export growth available at SITC (2 digit, Revision 3), I follow a probability based concordance. I use concordance tables from UN Stats[25].

For each NACE code, I look at the probability of a ISIC Rev 3 code getting mapped into NACE. For instance, if 1541 ISIC 3 maps into 1071 NACE, and 1552 ISIC gets mapped into 1102, then at 2-digit, code 15 of ISIC maps into 10 of NACE with probability 0.5, and code 11 of NACE with probability 0.5. I do the same for mapping ISIC Rev 3 to SITC Rev 3. Finally, I multiply the two probabilities to get an aggregate probability with which each 2-digit SITC code maps into 2-digit NACE code.

[25] https://unstats.un.org/unsd/cr/registry/regot.asp?Lg=1

Next, I multiply the export value for each 2-digit SITC code with the probability with which it maps into a NACE code. For each 2-digit NACE code, I sum up the weighted value of exports in a given year. The main assumption in this mapping procedure is that if 3650 SITC maps into 15 NACE, and 3630 SITC maps into NACE 14, then 36 maps into 15 and 14 with probability 0.5. I assume that the export value associated with code 36 of SITC has the same weight for 14 and 15, while in reality they might be different.

B.2 Calculating TFP, marginal cost, and markups

Firm level output and input price index

In ESEE, firms are asked to report the average transaction price (effective price) changes introduced from the previous to the reporting year in percentage points, for its activity optionally broken down in upto five markets. ESEE computes a global percentage change of the prices of the firm across markets for each year using a Paasche type formula using share of sales in the corresponding market as a weight. To compute a price index, I compute recursively from the percentage variation:

$P_{jt} = P_{jt-1}(1 + \%pricevariation_t/100)$

with $P_{jt} = 1$ for $t = 1990$ for all firms. For firms that enter after 1990 or when for one firm some intermediate rate of price growth is missing I impute from industry year average. I do the same for input price changes that occurred during the year for materials, which includes raw materials, parts, and energy, and services.

TFP

Following Ackerberg et al. (2015), I estimate a translog production function which relates the log value of output to the log value of capital, labour, and materials (including squared terms and all interactions) for eleven industry groups. I aggregate industry groups in the survey data at the level at which capital deflators are available from EU KLEMS. In the first stage, I obtain estimates of expected output using a translog function. The second stage relies on a law of motion of productivity, uses GMM techniques and relies on block bootstrapping for the standard errors to provide estimates for all production function coefficients. Anticipating the application of this paper, I allow input coefficients to vary by R&D intensity, R&D status following Doraszelski and Jaumandreu (2013), exporter status, and number of product innovations.

For the estimation, physical output is measured as sales deflated by price index calculated above. Labour is defined as number of employees, and capital input is defined as tangible fixed assets which is instrumented by investment expenditure of a firm following Collard-Wexler and De Loecker (2016). Capital is deflated by capital deflators sourced from EU KLEMS. Materials are defined as intermediate inputs deflated by input price index calculated above. I use data from 1990 to 2014 for this estimation.

Marginal cost and markups

I follow the method proposed by De Loecker and Warzynski (2012) to measure markups. The method builds on the insight that output elasticity of a variable factor of production is equal to its expenditure share in total revenue only when price equals marginal cost of production. Under any form of imperfect competition, a markup will drive a wedge between the inputs revenue share and its output elasticity and thus will be equal to

$$\mu_{it} = \theta_{it}^{X} / \alpha_{it}^{X}$$

where θ_{it}^{X} is the output elasticity of input X and α_{it}^{X} is the share of expenditures on input X_{it} in total sales of firm i at time t. Output elasticity of input is obtained by estimating a production function that gives an unbiased estimate of the output elasticity of a variable input. I use the production function approach described above, and calculate output elasticity for materials. Since, the expenditure share for input X is not directly observable, I follow De Loecker and Warzynski (2012) to correctly calculate expenditure share for materials, and then use it to divide output elasticity to calculate markups.